Beyond Efficiency: Understanding Job Candidates' Acceptance of AI-enabled Recruitment: A Socio-Technical Perspective

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Abstract

Artificial Intelligence (AI) is increasingly reshaping recruitment processes by automating candidate screening, interviews, and hiring decisions. Despite its growing adoption, AI-enabled recruitment tools raise significant ethical and psychological concerns among job candidates, particularly regarding fairness, transparency, risk, and trust. Addressing a notable research gap concerning candidate perspectives, this study aims to investigate job candidates' acceptance of AI-enabled recruitment tools, examining how perceived usefulness, ease of use, fairness, transparency, and risk influence their attitudes, mediated by trust and moderated by AI experience. Drawing on the Technology Acceptance Model (TAM), the Unified Theory of Acceptance and Use of Technology (UTAUT), and the Fairness, Accountability, Transparency, and Explainability (FATE) framework, the study introduces a socio-technical conceptual model to address the identified research gap. A quantitative survey was conducted with 143 job applicants in Jordan's pharmaceutical sector. The data were analysed using SPSS multiple regression analysis to assess the relationships among the variables. The findings show that perceived fairness, transparency, usefulness, and trust significantly shape positive attitudes toward AI-enabled hiring. Whereas ease of use and risk perceptions are less influential, trust proved to be a vital mediator, particularly between job applicants' perceptions of fairness and transparency and their attitudes toward AI-enabled recruitment tools, while prior AI experience moderates the influence of transparency and risk perceptions. The study concludes that respondents placed greater importance on AI's ethical and relational characteristics than technical functionality, highlighting the importance of designing functionally efficient, but also ethically responsible, fair, trustworthy, and transparent AI-enabled recruitment tools to promote candidates' acceptance and enhance responsible AI adoption in emerging labour markets.

Key words

IT adoption, AI in recruitment, trust in AI, ethical AI adoption.

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Introduction

Artificial Intelligence (AI) is reshaping the future of work and continues to be the climax of contemporary digital transformation (Moravec et al., 2024). In Human Resource Management (HRM), AI is significantly altering how organisations attract, engage with, develop, and select talent. Particularly in HR recruitment and selection, AI is broadly utilised in automating its tasks such as screening applications, conducting virtual instant interviews, and performing predictive hiring decisions, resulting in enhanced efficiency and consistency of hiring decisions (Deepa et al., 2024). However, despite their promise of greater objectivity and scalability, AI-enabled recruitment systems pose essential socio-technical challenges, particularly concerning user perceptions of fairness, transparency, risk, and trust (Glikson & Woolley, 2021; Kelly et al., 2023). These concerns are critical for job candidates, whose experiences with AI systems could influence specific outcomes relevant to them, such as hiring decisions and broader judgment of legitimacy, equity, and organisational ethics (Hilliard et al., 2022; Mirowska & Mesnet, 2022).

Despite the cumulative body of literature tackling AI applications in HR recruitment, several critical gaps remain. The most notable limitation is the excessive emphasis on managerial and organisational-level perspectives, stressing algorithmic efficiency and bias mitigation from the employer's viewpoint. The literature concentrates on HR professionals, systems designers, and organisational outcomes of AI adoption, bypassing the front-end experience of job candidates whose perceptions as the primary subjects of recruitment are underrepresented (Ore & Sposato, 2022; Rigotti & Fosch-Villaronga, 2024).

Consequently, despite their critical role as primary users, there is a notably insufficient exploration of job candidates' perceptions of AI-enabled recruitment and empirical studies focusing specifically on their perspectives. This gap undermines the efforts to fully understand the human implications of AI-enabled recruitment. It creates a noteworthy gap in understanding how job candidates, particularly in developing markets, perceive and engage with AI-enabled recruitment systems. In other words, AI-driven recruitment tools are increasingly being adopted. However, our understanding of their reception by job candidates remains limited, particularly regarding trust and ethical concerns in non-Western contexts such as Jordan.

To address this gap, this study investigates candidates' perceptions of AI-enabled recruitment, particularly their perceived functionality, fairness, risk, transparency, and trust as fundamental factors key to shaping their acceptance of such systems. By incorporating ethical, functional, and contextual actors, the study integrates theoretical constructs into a candidate-centric conceptual framework from a socio-technical perspective while investigating the mediation role of trust not as merely a static predictor, but as a dynamic influence shaped by AI systems' characteristics (Bedué & Fritzsche, 2022; Wanner et al., 2022) while considering the moderating role of user familiarity and experience with AI technologies.

To achieve the study aim, we intend to accomplish the following research objectives:

1. Assess how job candidates perceive AI-enabled recruitment tools' fairness, functionality, transparency, and risk.
2. Examine the mediating role of trust in shaping candidate attitudes toward AI-enabled recruitment.
3. Explore the moderating role of AI familiarity and experience in these relationships.

Accordingly, this study addresses the following research questions:

- RQ1: How do job candidates perceive the functionality, fairness, transparency, and risk of AI-enabled recruitment tools in Jordan?
- RQ2: How does trust mediate the relationship between these perceptions and their attitude toward AI-enabled recruitment?
- RQ3: How do user familiarity and experience with AI moderate these relationships?

Grounded in the Unified Theory of Acceptance and Use of Technology (UTAUT), the Technology Acceptance Model (TAM), and Fairness, Accountability, Transparency, and Explainability (FATE framework) (Davis, 1989; Shin, 2020; Venkatesh et al., 2003), the study offers empirical insights from the Jordanian context, which is characterised by high youth unemployment, a challenging digital transformation setting, and a nascent interest in utilising AI tools in public and private sector hiring practices.

Drawing on data collected from the job candidates, the study offers evidence of their perceptions of AI-enabled recruitment, enriching the limited body of literature from developing non-Western labour contexts (Hu et al., 2024; Lashkari & Cheng, 2023). It advocates shifting from technologically deterministic models to socio-technical frameworks that emphasise trust-aware, ethical, and equity-focused AI design and implementation in real-world hiring settings. From a policy standpoint, the study informs Jordanian public and private institutions and technology providers about the ethical and operational prerequisites for deploying AI in employment. The study aligns with SDG 8: "Decent Work and Economic Growth", specifically, SDG target 8.5 that endorses equal opportunity for all through the development of responsible AI tools that promote inclusive and equitable access to employment opportunities, particularly for youth and marginalised groups (Figueroa-Armijos et al., 2023; United Nations, 2015).

1. Literature review

1.1 Introduction to AI in Recruitment

AI refers to a broad set of technologies that empower systems to imitate human-cognitive functions such as reasoning, learning, and decision-making (Tambe et al., 2019; Wang, 2003) using machine learning (ML) techniques, which simulate the human brain's capacity to process immense and complex information (Deepa et al., 2024; Wang, 2003). While minimising or neutralising human intervention, the goal is to instantaneously perform autonomous decision-making (de Visser et al., 2018) with minimal effort.

Defining AI remains contentious across academic, governmental, and public domains despite its proliferation. Many technologies referred to as 'AI', like smartphones or smart cars, lack the adaptive autonomy of true AI, leading to confusion around what users are actually interacting with. This definitional ambiguity or oversight complicates AI acceptance studies since users' understanding of AI may diverge from its actual technological capabilities (Kelly et al., 2023). For clarity, AI can be categorised into three types: Artificial Narrow Intelligence (ANI), which includes most of current systems like Siri or Goggle Home; Artificial General Intelligence (AGI), which remains theoretical; lastly, Artificial Super Intelligence (ASI), which could one day exceed human intelligence (Bringsjord, 2011; Omohundro, 2014; McLean et al., 2020); cited in (Kelly et al., 2023).

In HRM, AI is widely adopted for continuous development and enhancing efficiency of the HRM functions through processing data collected from various external and internal sources, such as social media, job portals, performance metrics, and historical records to support recruitment, performance evaluation, training, retention, and competency mapping (Deepa et al., 2024). Particularly in recruitment, AI-enabled tools are used for screening resumes, automated interviews, and predictive hiring algorithms, which empower organisations to process an enormous number of job applications while limiting subjectivity in hiring decisions (Allal-Chérif et al., 2021; Deepa et al., 2024).

1.2 AI Role in Prompt Hiring Processes and Candidates' Experience

Adopting AI in HR recruitment processes has significantly impacted its consistency, scalability, and swiftness. For instance, it is argued that AI-enabled video interviews significantly improve the objectivity of applicant evaluation and reduce judgmental human bias (Allal-Chérif et al., 2021; Deepa et al., 2024). Chatbots and virtual assistants improve candidates' experience through instant, real-time, and personalised interactions. Additionally, Explainable AI (XAI) which refers to the degree to which an AI technology can explain its reasoning, decisions, and outputs in a way that is comprehensible to humans are being developed to boost job candidates' trust by enhancing AI's transparency, fairness, and usability in hiring decisions (Deepa et al., 2024; Robert et al., 2020).

While AI's advantages are widely recognised, its success in recruitment is dependent on end-users' perceptions and acceptance, particularly job candidates, who directly interact with AI hiring tools. While perceived usefulness, ease of use, and trust significantly influence the behavioural intention to adopt AI (Kelly et al., 2023), job candidates often question the fairness and transparency of AI decision-making, especially when interacting with automated interviews or algorithmic screening tools. Studies also suggest that perceived dehumanisation and a lack of feedback can undermine trust, even when AI appears technically efficient (Mirowska & Mesnet, 2022).

This reinforces the argument that user acceptance is highly contextual (i.e., context-sensitive nature) and cannot be detached from the cultural, demographic, and social environment in which the AI operates, as suggested by Sheng et al. (2008), who argued that technology adoption varies based on cultural and demographic contexts. A nuanced understanding of how users define and perceive AI is essential, since acceptance may be shaped not merely by the actual system characteristics but also by what individuals believe it to be (Kelly et al., 2023).

Much of the existing literature concentrates on 'managerial' competencies required for AI-HR integration, such as digital literacy, social capital, and decision-making agility (Deepa et al., 2024). However, this managerial focus often overlooks the candidate's perspective, the very individuals whose engagement contributes to the system's effectiveness. AI adoption in HRM cannot be evaluated solely on back-end efficiency; it must also consider the front-end user experience. Candidate perceptions of competence, benevolence, and integrity in AI interactions are essential to building trust and sustaining employer brand value (Kelly et al., 2023).

Furthermore, studies suggest that human oversight remains crucial in highly 'automated' systems, particularly in ethically sensitive areas such as HR recruitment (De Visser et al., 2018; Kaplan & Haenlein, 2019). Therefore, AI should not be considered as replacing human decision-making, but rather as a tool that augments inclusive and thoughtful recruitment practices. Understanding candidate acceptance enables not only the ethical deployment of AI but also its practical value across real-world recruitment scenarios.

1.3 Theoretical Foundations

Investigating candidates' perception and acceptance of AI-enabled recruitment systems necessitates a multidimensional approach that integrates functional and ethical considerations. This study is based on three main theoretical frameworks: TAM, UTAUT, and the FATE, which jointly offer a comprehensive foundation for understanding the technical, ethical, and socio-contextual factors that influence candidate acceptance of AI-enabled recruitment.

Among the earliest widely accepted information technology adoption models are TAM and UTAUT. The TAM framework (Davis, 1989) explains users' adoption of new technologies mainly using two predictors, namely, Perceived Usefulness (PU), which measures users' perception about the functional competence and Perceived Ease of Use (PEU), which reflects their perception of system usability and ease of interaction. PU and PEU positively influence attitude, which in turn is positively associated with intentions and eventually with the actual use (adoption). Meanwhile, UTAUT (Venkatesh et al., 2003) extends this premise by adding social influence, which is social pressure in the form of users' perception of whether influential others believe they should use the system. Hedonic Motivation measures the extent to which using the technology is enjoyable, and facilitating conditions reflecting individual beliefs about the organisation's technical infrastructure to support the system application (Venkatesh et al., 2003). Moreover, UTAUT incorporated mediating factors such as experience and age.

Several studies have utilised TAM and UTAUT to investigate AI adoption. PU, for instance, has been consistently considered the strongest predictor of attitude towards AI applications in HRM across sectors, which in turn positively affects their intention to adopt AI when they believe it potentially positively impacts HRM productivity, scalability and objectivity of hiring (Ibrahim et al., 2025). Further, organisational support positively influenced PU and PEU, contributing to greater augmented AI acceptance among HR professionals (Prikshat et al., 2025). Another finding (Herzallah

& Makaldy, 2025) showed that PU and PEU are significantly influenced by psychological attributes such as mindset and self-efficacy. Other studies applied UTAUT to examine how individual, environmental, and technological factors influence the acceptance of AI, validating UTAUT predictors, especially effort and performance expectancy, which correspond with TAM PU and PEU (Ali et al., 2024).

Some scholars (Prikshat et al., 2025) incorporated additional contextual variables, such as HR effectiveness and organisational support, which have proven to support TAM and UTAUT prediction of AI-enabled hiring systems adoption. Meta-analysis has shown that these constructs consistently predicted the attitude and behavioural intention toward using AI applications (Ali et al., 2024). Hence, this study hypothesises:

H1: Perceived Usefulness (PU) positively affects job candidates' Attitudes (ATT) toward AI-enabled recruitment.

H2: Perceived Ease of Use (PEU) positively affects job candidates' Attitudes (ATT) toward AI-enabled recruitment.

1.4 Candidate-Centric Constructs: FATE Framework Ethical and Relational Dimensions

While TAM and UTAUT concentrate on system usability and functionality, they neglect addressing ethical concerns. Consequently, the FATE framework (Shin, 2020) is incorporated to account for the non-functional ethical characteristics such as fairness, transparency, risk, and trust, which are critical concerns in investigating AI-enabled hiring. The FATE lens enables moving further beyond technical efficiency and examining how perceived ethical attributes of AI-enabled systems influence user acceptance and attitude (Bedué & Fritzsche, 2022; Wanner et al., 2022).

Shin's study showed that candidates are more likely to perceive it as useful, trust it, and be willing to accept AI decisions when they believe it is fair, accountable, transparent, and explainable.

Perceived fairness (PF) is the degree to which users view the decision-making processes and outcomes to be justful, which is commonly classified into procedural fairness (process fairness), distributive fairness (outcome fairness), and interactional fairness (dignity and information sharing in decision-making) (Ochmann et al., 2024; Xiong & Kim, 2025).

In HR recruitment and selection, candidates may sense AI fairness dimensions differently. Studies argued that the lack of social presence and behavioural control may decrease the job candidates' fairness perception and comfort with these tools (Hilliard et al., 2022). In other words, algorithmic systems often struggle with interactional and procedural fairness resulting from the limited transparency and the absence of human empathy (Ochmann et al., 2024). Other studies suggest that user expectations, system design, and ethical safeguards make fairness perception highly dependent on contextual features (Shin, 2020). Hence, it is essential to cite that algorithmic fairness highly depends on technical precision and users' cognitive and emotional judgments of an AI system's behaviour. This is illustrated by how users' thoughts of trust, accountability, transparency, and explainability portray a basic heuristic for engaging with and accepting personalised AI systems (Shin, 2020).

Another critical factor and complication of adopting AI in recruitment is the challenge of ethical bias. While AI is thought to eliminate human bias, resulting in more neutrality and objectivity, evidences suggest that it can learn from biased data, thus develop or even strengthen discriminatory patterns by inheriting and amplifying existing biases in historical data (Hunkenschroer & Luetge, 2022). A famous real-world illustration is Amazon's discontinued AI-enabled recruitment tool, which was shown to penalise resumes that had the word "women" or referenced only women's colleges (Dastin, 2022). Binns (2018) highlights the complexity of the concept of fairness, with contesting definitions driven by political philosophy, such as treatment equality versus outcome equality, complicating the implementation of fair AI systems in sensitive contexts.

Empirical findings have shown that XAI methods can mitigate these effects (Haque et al., 2023; Hofeditz et al., 2022; Wanner et al., 2022). Hofeditz et al. (2022) argued that increased algorithmic recommendations transparency reduces discrimination against women and older applicants.

However, they found that ‘explanation’ in AI systems could also unintentionally lower selection rates of racial minority groups, in particular when XAI is poorly contextualised.

Araujo et al. (2020) emphasised that the perceptions of fairness are contingent on the domain and affected by individual characteristics such as education, self-efficacy, experience, privacy concerns, and values. At the same time, it is worth noting that the individual disparities in accepting Automated Decision-Making (ADM) vary based on Socio-Technical factors, a distinct variation in AI-trust in low-stakes contexts, such as media, advertising, and consumer tech, versus high-stakes contexts, such as healthcare, finance, and security systems (Araujo et al., 2020).

As far as procedural justice is concerned, the literature underscores the importance of procedural justice and uncovers that granting users increased power and control over outcomes improved their perceptions of fairness, while simply explaining fairness principles did not have such an effect (Lee et al., 2019). This observation confirms Wang et al. (2020), who described a ‘favourability bias’ where individuals perceive algorithmic decisions to be fairer based on fairness-related consequences and outcomes, regardless of statistics or bias prevention measures.

Interactional fairness describes the relational component, which is often neglected in AI-enabled recruitment systems. Investigations by Kim and Heo (2021) and Nørskov et al. (2019) of AI video interviews, although being viewed as efficient and procedurally fair, candidates expressed discomfort due to the absence of social presence and human empathy. Interestingly, in some cases, job candidates rated robot-mediated interviews as fairer than human ones, implying that their impartiality and objectivity perception could outweigh or offset the lack of connectivity; however, this is not a common presumption among HR professionals who emphasise efficiency over ethical equity.

Ochmann and Laumer (2019) assert that when determining whether to adopt or trust AI in hiring, stakeholders evaluate fairness from multiple dimensions: ethical alignment, explainability, diversity, inclusion, and non-discrimination. Teodorescu et al. (2021) framing goes beyond technical fairness metrics to sociotechnical frameworks that ground fairness strategies to particular recruitment and users’ contexts, proclaiming that the best path to fairness is through augmented human–AI methods such as informed reliance and proactive oversight. Hence, AI and humans are required for fairness, and neither one alone could guarantee fairness.

These insights indicate that the fairness of AI-enabled recruitment systems and interventions should be multi-dimensionally conceptualised, covering system ethical perspectives (bias mitigation, XAI), procedural justice, user transparency, and socio-emotional dimensions. Once these issues are addressed, AI systems can earn legitimacy and trust that can eventually move the dial on candidates’ behavioural outcomes, including application intent, engagement, and advocacy. Consequently, the study hypothesises the following:

H3: Perceived Fairness (PF) positively affects job candidates' Attitudes (ATT) toward AI-enabled recruitment.

AI transparency is a key building block to establish trust and promote positive user perception (Bedué & Fritzsche, 2022; Felzmann et al., 2019; Glikson & Woolley, 2020). Compared to prior technologies, AI systems' complexity, social implications, and unpredictability make trust-building a much more nuanced endeavour. Utilising the Extended Valence Framework, based on semi-structured interviews with professionals, Bedué and Fritzsche (2022) found transparency and explainability to be essential sub-dimensions, which allow for the delivery of meaningful insights into how AI systems operate.

The legal frameworks provide further context for understanding the role of transparency in AI adoption. Felzmann et al. (2019) identify and analyse two key components of transparency: prospective transparency, meaning information provided prior to a decision being made (the use of applicant data, for example), and retrospective transparency, which includes post-hoc explanations (such as the reasons for candidate rejection). It offers a relational perspective to transparency by arguing that the information provision should be understood as a type of communicative act occurring between AI developers and users (e.g., through interactive visual cues, amongst others) that is contingent upon contextual factors, including user literacy, industry standards, technical requirements, etc. In recruitment, this means moving from passive disclosure to engaged, user-centred design that allows both candidates and hiring professionals to interrogate and understand AI decisions.

Moreover, AbdulKareem et al. (2024) examine the adoption of ICT and social media tools for e-recruitment in Nigeria’s federal public sector. Their findings demonstrate that ICT adoption enhances transparency, trust, and efficiency in recruitment systems, particularly when supported by digital literacy. They also recognise internet self-efficacy as a moderator variable, and argue that users who feel more confident about their digital skills are more likely to have a positive perception of the transparency and trustworthiness of the recruitment systems. This underlines the need for capacity building and user training initiatives complementary to the adoption of IT in HR recruitment.

Angerschmid et al. (2022) studied how transparency has the potential to repair or enhance trust through the effects of fairness levels and types of transparency on AI-augmented decision-making. Their users' study showed that low perceptions of fairness and transparency do indeed decrease trust significantly. However, the inclusion of fairness and transparency based on feature importance or case-based reasoning can help reestablish some trust (Angerschmid et al., 2022). These issues are acute in a recruitment setting, where perceived decision-making bias or lack of transparency may result in potential candidates disengaging from the process or reputational damage for the organisations involved.

Another perspective is 'algorithmic vigilance' (Zerilli et al., 2022), a middle-of-the-road approach where users critically interact with AI outputs rather than rejecting them utterly, conceptualise trust in AI as a spectrum, with aversion (unwarranted scepticism) on one end and appreciation or loafing (uncritical overreliance) on the other. The findings underscore the importance of implementing task-sensitive and fixable strategies that address the users' needs and deliberate the decision-making contexts, such as HR recruitment. Consequently, AI-enabled recruitment systems should provide explanatory information and additional indicators, such as performance metrics, confidence levels, and error rates, to enable users to make well-informed and critically evaluated judgments about AI transparency.

These literatures provide strong, cohesive evidence that perceived transparency is essential in positively shaping users’ trust, attitudes toward AI, and intentions to engage with AI systems. Moreover, transparency should not be confined to technical disclosures; it must enable users to comprehend, critically engage with, and eventually trust AI-driven decisions by offering dynamic, communicative, and context-sensitive transparency, which in turn positively influences their attitude (Xiong & Kim, 2025). Accordingly, the study hypothesises the following:

H4: Perceived Transparency (PT) positively affects job candidates' Attitudes (ATT) toward AI-enabled recruitment.

Integrating AI with recruitment processes will likely raise perceived risk concerns, influencing users’ trust and attitude (Araujo et al., 2020; Lashkari & Cheng, 2023; Li, 2025). Perceived risk is commonly considered to have a significant negative impact on the perception of users' attitude and intention of technology adoption. It could weaken the effects of ease of use and perceived usefulness while amplifying the role of subjective norms (Chaudhary, 2024). In AI hiring, the perceived risk also involves apprehensions regarding algorithmic bias, fairness, transparency, loss of intuitive human judgment and that which influences trust and acceptance of these tools.

Moreover, Araujo et al. (2020) explored how AI fairness, usefulness, trust, and risk perceptions fluctuate across sectors (e.g., public health, media, and justice). Their findings showed that these factors are highly subject to individual characteristics and the contextual aspects (Larsson et al., 2024). The context-specific evidence shows that some participants showed agreeableness to rely on AI-driven output equivalent to human decisions in low-stakes contexts; on the other hand, scepticism prevailed in high-stakes contexts.

In the given context of recruitment, by interviewing recruiters and job candidates, Lashkari and Cheng (2023) investigated the phenomenon of AI-enabled recruitment, possible misjudgement, bias, and the absence of human interaction. The findings revealed that while job seekers emphasised the necessity of relationship-building, fairness, and human-centred interactions, recruiters focused on the cognitive bias and a desire for supportive technologies. These findings highlight the risk-trust dynamic, which in turn shapes the user's acceptance and intentions toward these AI-enabled recruitment methods.

Although focused on system design perspectives, empirical investigation of Li (2025) reinforced these conclusions and found that perceived anxiety and risk exert a significant adverse effect on system designers' intentions to adopt AI-generated content (Rigotti & Fosch-Villaronga, 2024). These findings can be extrapolated to the recruiting context where perceived risk erodes trust and, in turn, negatively impacts the likelihood of a candidate's acceptance of AI-enabled recruitment.

The existing literature across different disciplines confirms the adverse effect of perceived risk in AI systems acceptance, particularly in high-stakes contexts such as recruitment. Accordingly, the study hypothesis:

H5: Perceived Risk (PR) negatively affects job candidates' Attitudes (ATT) toward AI-enabled recruitment.

Although often used interchangeably in technology adoption literature, to further explain the conceptual design of this study, it is crucial to conceptually and theoretically distinguish between trust in AI and attitude toward AI-enabled recruitment systems, given their distinct roles in shaping job candidate acceptance. Trust in AI is a multi-faceted, belief-based construct that represents a user's perspective on how much they can and are willing to rely on an AI system in situations of uncertainty or vulnerability (Glikson & Woolley, 2020; Lee, 2018). Trust is known to be based on the perception of system competence, integrity, and benevolence (Bedué & Fritzsche, 2022; Mayer et al., 1995). Therefore, in this study context, trust implies that the user believes that the AI-enabled recruitment functions operate with competence, integrity, and benevolence and are in accordance with ethical expectations, even without granting complete transparency or control.

In contrast, attitude toward AI is another wider form of judgment as a general evaluation of users' positive or negative feelings about using technology (Davis, 1989, 2023; Li, 2025), which in this study context, is AI-enabled recruitment tools. Attitude is an affective-cognitive disposition that includes beliefs, emotions (e.g., comfort, anxiety), and behavioural tendencies (e.g., willingness to accept AI decisions).

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This conceptual differentiation allows for a more precise examination of the pathway, where perceived fairness and transparency boost trust, which in turn positively shapes attitude toward AI-enabled recruitment. Such a pathway has been supported in empirical studies by Wanner et al. (2022), Xiong and Kim (2025), and Shin (2020), who emphasise the mediating role of trust in technology acceptance, particularly in ethically sensitive domains like hiring. Establishing this distinction between trust theory and attitude enhances the conceptual framework's explanatory clarity and empirical robustness.

When investigating the adoption and acceptance of AI in HRM, trust has been identified as a key construct (Bedué & Fritzsche, 2022; Figueroa-Armijos et al., 2023; Lee, 2018; Rukadikar & Khandelwal, 2024; Wanner et al., 2022). From initial resume screening to final-phase interviews, AI systems are progressively becoming integrated into recruitment processes. The effectiveness of such tool's hinges not only on their technical competence but also on the extent to which users trust them. The notion of trusting the process is at its core based on the principle of perceived transparency, which emerged as a normative ethical expectation and a determinant of acceptance and engagement (Ogunniye et al., 2021). Bedué and Fritzsche (2022) shed light on the need for self-imposed standards and multi-stakeholder responsibility, particularly in high-impact areas such as recruitment, suggesting that trust has three interrelated dimensions: competence, integrity, and benevolence.

In their contribution, Glikson and Woolley (2020) conducted a multidisciplinary review of empirical research on AI trust. They distinguish cognitive trust from perceptions of the AI system's reliability, responsiveness and transparency, and emotional trust shaped by anthropomorphising traits and perceived intent. This two-tiered model of collation trust is present in recruitment, where job seekers and HR professionals desire both procedural clarity and emotional assurance of AI decision-making that aligns with human values and is devoid of implicit biases. Rukadikar and Khandelwal (2024) argued that while HR professionals generally trust AI-enabled tools like chatbots, data privacy and cultural alignment persist as obstacles. Thus, the study hypothesis:

H6: Trust in AI (TRS) positively affects job candidates' Attitudes (ATT) toward AI-enabled recruitment.

Moreover, trust might mediate between perceptions of AI characteristics, such as fairness, transparency, and explainability, and job candidates' attitudes toward it (trust-outcome relations). Several empirical studies confirm the intermediary role of trust (Ogunniye et al., 2021). Job candidates' trust increases when AI systems are generally perceived as transparent and fair, and AI perceived risk diminishes, resulting in more positive attitudes towards the organisation and hiring process. Moreover, trust mediates the relationship between AI explainability and candidate receptiveness, especially if the system is clear on "how" and "why" explanations (Xiong & Kim, 2025).

Consistent with this proposed mediating effect, Shin (2020) found that candidates who perceived AI systems as accountable and transparent exhibited increased satisfaction and engagement. Wanner et al. (2022) adopted a UTAUT-based model and found that transparency increases trust, which in turn enhances performance perception and adoption possibilities. Likewise, Bedué and Fritzsche (2022) stressed that trust, defined by the competence, integrity, and benevolence perceptions, plays a mediating role between transparency and the behavioural intention of adoption.

Ethical and organisational factors also contribute to trust. Figueroa-Armijos et al. (2023) associated performance expectancy with ethical perceptions of the AI, hence supporting organisational trust. From this perspective, the study hypothesis:

H7: Trust (TRS) in AI mediates the relationship between Perceived Fairness (PF) and Attitude (ATT) toward AI-enabled recruitment.

H8: Trust (TRS) in AI mediates the relationship between Perceived Transparency (PT) and Attitude (ATT) toward AI-enabled recruitment.

H9: Trust (TRS) in AI mediates the relationship between Perceived Risk (PR) and Attitude (ATT) toward AI-enabled recruitment.

Taken together, these findings demonstrate that trust in AI-recruitment is multi-dimensional and is shaped by system attributes (e.g., competence, integrity, and benevolence), contextual factors (e.g., organisational readiness, culture), and user perceptions (AbdulKareem et al., 2024; Angerschmid et al., 2022; Haque et al., 2023). Future research is needed to further clarify the complex pathways of trust's impact on AI acceptance and adoption while considering the contextual attributes in culturally diverse and ethically sensitive domains.

Although trust is assumed to mediate user attitudes toward AI in recruitment, their experience with AI can also act as a moderating factor shaping the extent to which perceived ease of use, trust, and other constructs influence their attitude towards AI. Studies conducted in culturally diverse settings highlighted digital exposure as a significant moderating factor (Upadhyay & Khandelwal, 2018).

Grounded on the extended UTAUT model, Tanantong and Wongras (2024) and Wongras and Tanantong (2023) investigated AI-enabled recruitment in Thailand. Their findings revealed earlier exposure or familiarity with AI technologies moderated the effect on effort expectancy and perceived usefulness. Ismatullaev and Kim (2022) confirmed these findings, showing that trust, fostered by transparency and simplicity, significantly enhances usability perceptions. Thus, this relation is even more substantial among users with AI experience. On the other hand, Glikson and Woolley (2020), in their two decades of research review, underlined that cognitive and emotional trust are driven by system anthropomorphism, reliability, and the context of use, which are factors that are more striking among experienced users.

In experimental research, Lee (2018) found that although people perceived algorithmic decisions as efficient, they were less trusted than human decisions, especially in empathy-demanding roles. These findings suggest that familiarity is imperative in relation to expectations, social norms, and perceived risks. Further, ease of use, perceived fairness, transparency, and explainability are some of the main domains in which user experience interferes with acceptance. Studies by Haque et al. (2023) and Angerschmid et al. (2022) showed that users' previous exposure to AI would enhance their responsiveness to clear, human-like instructions, hence showing more acceptance. From this viewpoint, the study hypothesis:

H10: AI Experience moderates the relationship between Perceived Ease of Use (PEU) and Attitude (ATT) toward AI-enabled recruitment, such that the relationship is stronger among those with higher experience.

H11: AI Experience moderates the relationship between Perceived Fairness (PF) and Attitude (ATT) toward AI-enabled recruitment, such that the relationship is stronger among those with higher experience.

H12: AI Experience moderates the relationship between Perceived Transparency (PT) and Attitude (ATT) toward AI-enabled recruitment, such that the relationship is stronger among those with higher experience.

H13: AI Experience moderates the relationship between Perceived Risk (PT) and Attitude (ATT) toward AI-enabled recruitment, such that the relationship is stronger among those with higher experience.

1.5 Justification for the Proposed Framework: Integrated Socio-Technical Framework

When investigating HR recruitment through controversial means such as AI, it is crucial to note that attitudes are hardened by concerns over fairness, risk, loss of human touch, and algorithmic ambiguity, provoking scholars to integrate trust and other social factors as predictors or mediating variables. Such a holistic approach enhances our understanding of adoption phenomena through a similar predictive intersection of TAM and UTAUT characteristics.

While TAM and UTAUT models have been widely applied in explaining the adoption and acceptance of AI across organisational settings (Ore & Sposato, 2022; Rigotti & Fosch-Villaronga, 2024), this study considers their constructs from a user-centric perspective, specifically, job candidates. Contrasting organisations, employees or managers who may be introduced appropriately, receive training or other organisational support to adopt IT systems, job candidates' experience with AI-enabled recruitment systems is mostly a one-time, consequential interaction that lacks institutional support. Therefore, this context mandates expanding the earliest models to incorporate social and ethical constructs which are under-theorised in early technology adoption theories.

Consequently, grounded on TAM, UTAUT, and FATE literature, this study addresses these gaps by proposing an integrative framework (Figure 1).

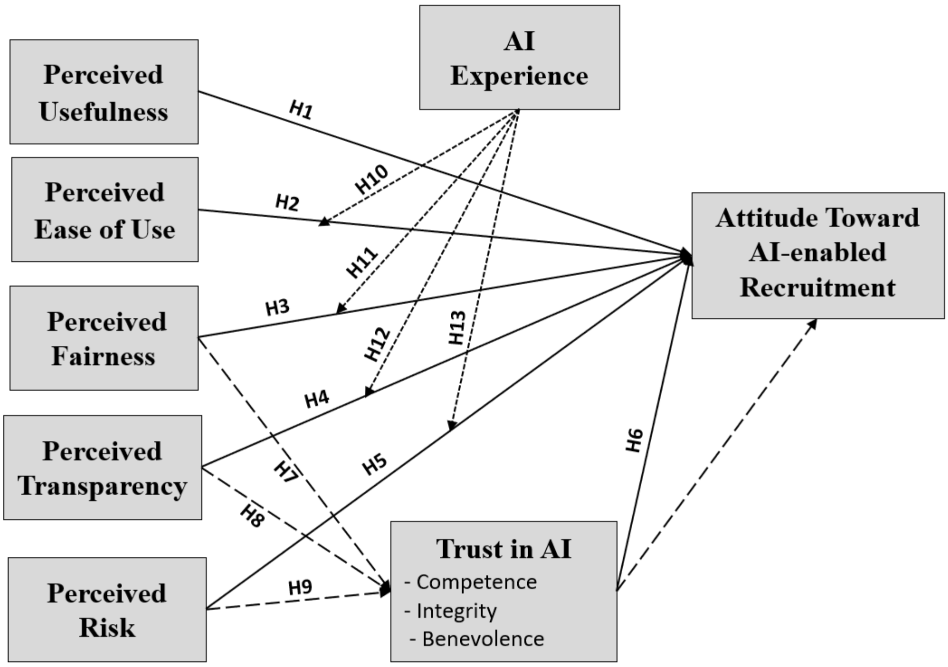

Figure 1. Study Framework.

Note: Solid line for direct effects (H1–H6), dashed line for mediation effects (H7–H9), dotted line for moderation effects (H10–H13).

Source: Author's elaboration.

This framework is well-suited to achieve the study objectives and capture the candidate perspective by exploring how perceived usefulness, ease of use, and external variables, namely perceived fairness, transparency, risk, and trust, influence job candidates' attitudes toward AI-enabled recruitment. Meanwhile, introducing trust as a fundamental mediating variable and experience as a moderator, the framework facilitates the explanation of variations in candidate acceptance that traditional models have not fully addressed.

This enhanced framing contributes to the academic literature as it further bridges the gap by re-centring the focus on candidates whose perspective is often neglected in AI adoption research. It also contributes to theoretical integration by combining perceptual and behavioural constructs in recognised technology acceptance models. The framework offers organisations a structured guide to designing transparent, ethical, and user-friendly AI-enabled recruitment systems which are more likely to be trusted and accepted by job applicants.

2. Methodology

2.1 Instrument and Data Collection

Considering this study's exploratory and descriptive nature, a questionnaire-based quantitative research approach was employed. An online questionnaire following Sekaran and Bougie's (2016) recommendations was developed and administered among job applicants. The questionnaire's primary objective was to measure applicant attitudes and trust toward AI-powered tools in recruitment processes, particularly in screening and assessment contexts.

The questionnaire had two sections. The first collected demographic and sample characteristics, namely respondents' age (measured in terms of four age categories), educational level (four educational levels), and professional work experience (four experience scales). Besides, respondents' AI experience was measured using a structured single-item measure for which four clearly defined experience levels: "No Experience" (never used or directly interacted with AI technologies); "Limited Experience" (minimal or short-term familiarity and interaction with AI, for instance, occasional use);

"Moderate Experience" (recurring regular interaction and familiarity about basic AI capabilities, for example, generative AI, AI assistants, or chatbots); and "Extensive Experience" (high-frequency interaction and significant familiarity or occupational use of sophisticated AI tools). These items provided contextual and demographic information about respondents' backgrounds, where some are supposed to potentially affect their attitudes toward AI in the recruitment context.

The second section comprised structured items that measure the core constructs of the study, specifically a total of eight key constructs measured using 28 items. All construct items were scaled on a 5-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree). These measurement items are grounded on previously validated instruments used in the existing literature (see Table 1) and were revised and reworded minimally to fit this study's contextual and cultural context.

The constructs measures comprised Perceived Usefulness (PU), which was measured using three items measuring respondents' perception of AI's efficiency, accuracy, and quality in processing recruitment decisions; Perceived Ease of Use (PEU), which comprised three items measuring simplicity, user-friendliness, and ease of interaction with AI-powered recruitment tools; Perceived Fairness (PF), comprised three items measuring respondents' perception of AI impartiality and equally in recruitment decision; Perceived Transparency (PT), formed three items reflecting respondents' perception about the clarity and simplicity of AI's decision-making process; and Perceived Risk (PR), which was measured using three items assessing respondents' perception of data privacy, evaluation error, and misjudgement of AI-enabled recruitment.

Trust in AI (TRS) was conceptualised with three subdimensions: Competence, Beneficence, and Integrity (McKnight et al., 2002), each measured using three items. These subdimensions captured the respondents' trusting belief in AI's ability, ethical intentions, and reliability. Lastly, Attitude Toward AI in Recruitment (ATT) was measured using four items reflecting respondents' overall conception of the position and acceptance of AI-enabled recruitment decisions.

The questionnaire was developed in English and checked by HRM and information systems experts. A small sample pilot test was carried out to evaluate the instrument's coherence and clarity, which resulted in minor changes and improvements based on the feedback. The data were collected over a six-week period through a Google Forms link that was shared with job candidates through emails by hiring professionals involved in the recruitment process and who had access to the job candidates fitting the study criteria.

Table 1. Survey Constructs and References.

Construct	Items	Source(s)
Perceived Usefulness (PU)	3	Davis (1989); Venkatesh and Davis (2000)
Perceived Ease of Use (PEU)	3	Davis (1989); Venkatesh and Davis (2000)
Perceived Fairness (PF)	3	Shin (2020)
Perceived Transparency (PT)	3	Shin (2020); Langer et al. (2021)
Perceived Risk (PR)	3	Pavlou (2003); Shin (2020)
Trust in AI (TRS) – subdimensions:	9	
Competence	3	McKnight et al. (2002); Mayer et al. (1995); Glikson and Woolley (2020)
Benevolence	3	
Integrity	3	
Attitude Toward AI-enabled Recruitment (ATT)	4	Venkatesh et al. (2003)

Note: All items were adapted and reworded to reflect the context of AI-enabled recruitment.
Source: Author's elaboration.

2.1 Population and Sampling

Since this study investigates the notion of AI acceptance from the perspective of job candidates, the target population for this study comprised job applicants who had applied for job openings in three pharmaceutical companies in Jordan that employ sourced AI-enabled tools in their recruitment to process applicants' screening and evaluation processes and was carried out in December 2024. Specifically, the study targeted applicants for four different job positions, of which two were entry-level, namely logistics coordinator and pharmaceutical sales representative, and two were mid-level openings that require four years or more of professional experience in a similar role, namely Quality Assurance (QA) specialist and IT business analyst. The approximate number of total applicants was 1,056 for the four positions representing the accessible population for the study. Due to the practical restrictions associated with reaching job applicants directly, a convenient sampling method was adopted. The study questionnaire was shared by hiring professionals of participating companies through email. The correspondence included a cover letter outlining the study's purpose and objectives while asserting anonymous voluntary participation, explaining that their responses would only be utilised for research purposes. To avoid bias and ensure that responses reflected applicants' genuine perceptions while isolating the influence of hiring outcomes, the study was administered prior to the point at which applicants were notified about their employment decision outcome.

1.3 Sample Characteristics

A total of 143 valid responses were retained for the final data analysis. As shown in Table 2, the most significant proportion of respondents was below 25 years (51.7%), followed by 26–30 years (30.8%), and 30–40 years (14.0%), while merely 3.5% were 40+ years.

Table 2. Sample Characteristics.

Variable	Categories	Frequency	Percent
Age	Less than 25 years	74	51.7
	26–30 years	44	30.8
	30–40 years	20	14.0
	40 or older	5	3.5
Education	Bachelor	104	72.7
	Master/High Diploma	38	26.6
	Doctorate	1	0.7
Work Experience	None to less than 1 year	61	42.7
	2 - 5 years	42	29.4
	6 - 10 years	32	22.4
	10 Years and Above	8	5.6
Experience with AI	No Experience	8	5.6
	Limited Experience	32	22.4
	Moderate Experience	71	49.7
	Extensive Experience	32	22.4

Source: Author’s elaboration.

In terms of academic qualifications, 72.7% of respondents held a bachelor’s degree, 26.6% had a master's degree, while only 0.7% had a doctoral degree. Regarding work experience, the majority of respondents (42.7%) had minimal experience, with none to less than one year of experience. Additionally, 29.4% of respondents reported having 2 to 5 years of experience, and 22.4% had 6–10 years of experience. Lastly, only 5.6% of respondents reported over 10 years of experience, representing the smallest group. Moreover, the sample distribution in terms of respondents’ experience level with AI differed significantly. The largest proportion (49.7%) reported moderate experience with AI technologies, while minimal and intensive experience with AI technologies occurred equally, representing 22.4% of the study sample. The smallest group are those who reported no prior experience in AI technologies, at 5.6%. The entry and mid-level targeted job openings can rationalise this result.

1.4 Perception Differences Based on Demographics

As shown in Table 3, to examine the difference in perceptions of AI-enabled recruitment systems across demographic groups, specifically age, education level, and AI experience, one-way ANOVA tests were conducted on the framework key constructs: PU, PEU, PF, PT, PR, TRS, and ATT.

Table 3. One-Way ANOVA Results on Perceptions of AI-enabled Recruitment.

Construct	Age P-value	Education P-value	AIE P-value	AIE F-value	AIE Effect
PU	0.933	0.933	0.000	50.005	Large
PEU	0.813	0.813	0.000	50.943	Large
PF	0.34	0.34	0.000	71.244	Large
PT	0.89	0.89	0.000	53.037	Large
PR	0.65	0.65	0.000	6.825	Moderate
TRS	0.433	0.433	0.000	66.597	Large
ATT	0.571	0.571	0.000	95.844	Large

Source: Author's elaboration.

The analysis revealed the absence of statistically significant differences across the constructs based on age or education level. The p-values of all constructs were greater than the 0.05 threshold, indicating that respondents had similar perceptions regardless of their age or education level.

In contrast, for respondents' prior AI experience level, the analysis showed statistically significant differences across all with p-values less than $p < .001$. Tukey HSD tests revealed that individuals with more AI experience reported higher levels of PU, PEU, PF, PT, TRS, and ATT, along with lower levels of PR when compared to those with less or no experience.

Findings support the hypothesized moderating effect of AI experience on perceptions, implying that greater exposure and familiarity with AI may decrease scepticism and enhance acceptance, especially regarding AI-enabled recruitment perceived fairness, risk, and trust.

1.5 Measurement of Reliability and Validity

To assess the instrument's robustness and consistency, the constructs' convergent validity and internal consistency were examined. For convergent validity, a Confirmatory Factor Analysis (CFA) was performed, extracting factor loadings, Average Variance Extracted (AVE), and Composite Reliability (CR). In line with recommendations of methodological soundness (Hair et al., 2019; Chin, 1998), factor loadings with values greater than 0.50 were considered acceptable. Meanwhile, loading values over 0.7 are deemed ideal (Straub, 1989). Likewise, CR and AVE values beyond 0.80 and 0.50, respectively, are considered acceptable (Hair et al., 2019).

As shown in Table 4, item loadings exceeded the ideal threshold of 0.7. The CR values ranged from 0.882 to 0.958, while the AVE values ranged from 0.714 to 0.814. These results provide strong evidence of convergent validity across all measured constructs.

Table 4. Reliability and Convergent Validity.

Construct	Item	Loading	CR	AVE	Cronbach's a
Perceived Usefulness (PU)	PU1	0.87	0.914	0.780	0.859
	PU2	0.88			
	PU3	0.89			
Perceived Ease of Use (PEU)	PEU1	0.88	0.904	0.758	0.842
	PEU2	0.87			
	PEU3	0.86			
Perceived Fairness (PF)	PF1	0.89	0.929	0.814	0.884
	PF2	0.90			
	PF3	0.92			
Perceived Transparency (PT)	PT1	0.87	0.882	0.714	0.797
	PT2	0.89			
	PT3	0.77			
Perceived Risk (PR)	PR1	0.89	0.927	0.810	0.882
	PR2	0.90			
	PR3	0.91			
Trust in AI (TRS)	COM1	0.83	0.958	0.718	0.950
	COM2	0.86			
	COM3	0.85			
	BEN1	0.91			

	BEN2	0.87			
	BEN3	0.84			
	INT1	0.79			
	INT2	0.80			
	INT3	0.85			
Attitude (ATT)	ATT1	0.83	0.932	0.773	0.953
	ATT2	0.89			
	ATT3	0.90			
	ATT4	0.90			

Source: Author's elaboration.

Cronbach's alpha coefficients were extracted to assess the instrument's internal reliability. According to the accepted standards, values over 0.70 indicate a strong reliability (Hair et al., 2019). All constructs demonstrated Cronbach's alpha values ranging from 0.797 to 0.953, confirming the instrument's internal consistency.

Moreover, Fornell and Larcker's (1981) criterion was utilised to evaluate discriminant validity by comparing the square root of the construct's AVE with its correlations to other constructs. As shown in Table 5, the square root of the AVE exceeded its intra-construct correlations, with one exception.

Table 5. Discriminant Validity.

	PU	PEU	PF	PT	PR	TRS
PU	**0.883**					
PEU	0.866**	**0.871**				
PF	0.863**	0.850**	**0.902**			
PT	0.566**	0.570**	0.619**	**0.845**		
PR	-0.264**	-0.258**	-0.280**	-0.017	**0.900**	
TRS	0.821**	0.869**	0.863**	0.647**	-0.184*	**0.847**
ATT	0.859**	0.857**	0.891**	0.664**	-0.266**	0.877**

Note: *. Correlation is significant at the 0.05 level (2-tailed); **. Correlation is significant at the 0.01 level (2-tailed).
Source: Author's elaboration.

The TRS and ATT correlation was found to be 0.877, exceeding the square root of AVE for Trust constructs (0.847). As a result, this suggests a minor violation of the Fornell-Larcker criterion and possible overlap between the constructs. However, this finding is understandable in the context of the fundamental theory guiding the model. Trusting AI in recruitment is hypothesised to be a powerful prior condition for the individuals' attitude toward it. Thus, a robust correlation between the two constructs is not only anticipated but also theoretically well-grounded. Participants who trust AI systems in processing recruitment decisions may also rate them more positively and have highly aligned trust and attitude perceptions.

Additionally, respondents may have viewed their trust in AI as a fundamental component of their overall attitude, particularly when the assessment was performed through such technologies. This proximity of concepts might explain the higher correlation. Even though they crossed a statistical threshold, conceptually, they are still distinct constructs developed and measured with different, validated items.

Except for this single violation of Fornell and Larcker's (1981) criterion, the results confirm that the measurements show adequate discriminant validity and are perceived as empirically distinct constructs by the respondents.

3. Research results

3.1 Direct Effects

Hypotheses H1 to H6 relating to the direct effects of the presumed independent variables on the dependent variable, namely attitude toward AI-enabled recruitment (ATT), were tested using multiple regression using SPSS. As shown in Table 6, the overall R^2 for the model is 0.867, indicating that the six predictors explain 86.7% of the variance of the dependent variable (ATT).

Table 6. Model Summary

Model	R	R^2	Adjusted R^2	Std. Error
1	0.931a	0.867	0.861	0.37323756

Note: a. Predictors: (Constant), TRS, PR, PT, PU, PEU, PF.
Source: Author's elaboration.

Table 7 summarises the regression results for each hypothesis. As exhibited, Perceived Fairness (PF) had the most potent effect on ATT (β = 0.318, t = 4.172, p < 0.001), supporting H3. Likewise, Trust in AI (TRS) had a highly positive effect on attitude (β = 0.253, t = 3.351, p = 0.001), thereby supporting H6.

Table 7. Regression Results.

Hypothesis	Construct	R2	B	T-value	Sig.	Result
H1	Perceived Usefulness (PU)	0.738	0.194	2.715	0.007	Supported
H2	Perceived Ease of Use (PEU)	0.730	0.112	1.469	0.144	Not Supported
H3	Perceived Fairness (PF)	0.796	0.318	4.172	<0.001	Supported
H4	Perceived Transparency (PT)	0.443	0.128	3.023	0.003	Supported
H5	Perceived Risk (PR)	0.071	-0.048	-1.439	0.152	Not Supported
H6	Trust in AI (TRS)	0.768	0.253	3.351	0.001	Supported

Source: Author's elaboration.

Moreover, H2 is supported where Perceived Usefulness (PU) showed a significant positive effect (β = 0.194, t= 2.715, p = 0.007), Hypothesis H4 is also supported (β = 0.128, t = 3.023, p = 0.003), where Perceived Transparency (PT) has a moderate yet significant effect. In contrast, Perceived Ease of Use (PEU) (p = 0.144) and Perceived Risk (PR) (p = 0.152) effects were insignificant at the 0.05 level, thus rejecting H2 and H5. The findings highlight that fairness, trust, usefulness, and transparency influence candidates' attitudes toward AI-enabled recruitment. Conversely, ease of use and perception of risk appear less compelling, given this study's scope.

3.2 Mediation Effects

To evaluate whether TRS mediates the relationships between the predictors (PF, PT, and PR) and the independent variable (ATT), the PROCESS Macro Model 4 (Hayes, 2022) was employed with 95% confidence and 5,000 bootstrap samples. Summarised in Table 8, the indirect effect of PF and PT on ATT through TRS is significant (IE = 0.3595; 95%, CI 0.2198, 0.5431; IE = 0.4985; 95%, CI 0.3557, 0.6501, respectively), yet the direct effect is significant, which suggests a partial mediation effect and supports H7 and H8 (Table 5).

Table 8. Mediation Effect Summary.

Hypothesis	Path	IE	LLCI	ULCI	Mediation	Result
H7	PF → TRS → ATT	0.3595	0.2198	0.5431	Partial	Supported
H8	PT → TRS → ATT	0.4985	0.3557	0.6501	Partial	Supported
H9	PR → TRS → ATT	-0.1581	-0.3221	0.0862	No Mediation	Not Supported

Source: Author's elaboration.

This result demonstrates that while PF and PT had a significant direct effect on ATT, they also improved through the increased TRS. In contrast, the indirect effect of PR through TRS was insignificant (IE = –0.1581; 95% CI –0.3221, 0.0862), implying the absence of a mediating role of TRS in the PR-ATT relationship.

Overall, the results reveal that trust is a key mediating factor in shaping candidates' attitudes towards AI-enabled recruitment, specifically the perceived fairness and transparency of such AI tools.

3.2 Moderation Effects

To examine the AI-Experience (AIE) moderating role among the predictors, namely perceived ease of use (PEU × AIE), perceived fairness (PF × AIE), perceived transparency (PT × AIE), perceived risk (PR × AIE), and the attitude toward AI in recruitment, PROCESS Macro Model 1 was used. As shown in Table 9, the interaction effects of (PEU × AIE) and (PF × AIE) were not statistically significant (p =0.1725 and p =0.2553, respectively).

Table 9. Moderation Effects Summary.

Hypothesis	Moderation Path	Interaction p-value	Moderation Effect	Result
H10	PEU × AIE → ATT	0.1725	Not significant	Not Supported
H11	PF × AIE → ATT	0.2553	Not significant	Not Supported
H12	PT × AIE → ATT	0.031	Significant	Supported
H13	PR × AIE → ATT	0.0138	Significant	Supported

Source: Author's elaboration.

Thus, H10 and H11 are not supported. The results imply that the candidates' experience with AI does not significantly intervene in the effect of ease of use and fairness perceptions on their attitudes toward AI-enabled recruitment.

In contrast, H12 and H13 yielded strong moderation effects. The perceived transparency (PT × AIE) experience interaction was significant at (p=.0310), suggesting that the effect of perceived transparency (PT) on attitude becomes stronger among candidates with higher AI familiarity and experience. Similarly, AI Experience moderated the negative effect between perceived risk (PR × AIE) and attitudes toward AI-enabled recruitment (p = .0138). This means that for candidates with less AI experience, perceived risk had a stronger negative effect on their attitudes toward AI-enabled recruitment. However, this effect becomes weaker or natural when candidates are highly familiar with AI. Hence, accepting H12 and H13.

4. Discussion

The results offer both expected confirmations of existing literature and novel contributions that deepen the understanding of a candidate-centred AI-enabled recruitment acceptance.

The strong effect of trust as a direct predictor is consistent with prior findings and the increasing consensus in the AI literature on the notion that trust is a gateway to user acceptance (Bedué & Fritzsche, 2022; Shin, 2021), especially in sensitive contexts such as evaluating job applications and hiring decisions. This result aligns with Glikson and Woolley's (2020) and Wanner et al.'s (2022) assertion that trust in AI extends beyond technical functionality and encompasses integrity and fairness perceptions, also confirming trust as a dynamic construct sensitive to system attributes.

Similarly, the confirmed positive effect of perceived usefulness on a candidate's attitude validates the core TAM assumption (Davis, 1989). This finding confirms Prikshat et al. (2025) and Herzallah and Makaldy (2025), who also emphasised the role of perceived usefulness in predicting attitude toward using AI.

Interestingly, ease of use did not significantly appear to predict attitudes toward AI-enabled recruitment tools. Although ease of use is frequently cited as a primary antecedent in TAM literature (Davis, 1989), this result questions whether that system-user interaction maintains its conventional significance as an IT adoption predictor. This factor may be lessening in AI contexts such as Chatbots, Generative AI, or AI-enabled hiring tools, where complexity is lower and users' interaction with the system interface is effortless and limited.

Interestingly, perceived risk did not significantly predict attitude. These results suggest that perceived risk might reflect deeper structural concerns like system bias, data protection, or control imbalances, which solely trust cannot mitigate. It also may be indicative of the increasing normalisation of AI technologies among younger users or the sense of inevitability around algorithmic screening. This confirms Araujo et al.'s (2020) argument that risk perceptions fluctuate across sectors and contexts.

On the other hand, the confirmed positive effect of transparency validates the FATE framework, which suggests that the more users understand the functionality of AI systems, the more they hold a positive attitude toward them. This positive effect of perceived transparency on candidates' attitudes towards AI-enabled recruitment is consistent with existing theory and empirical research. The result confirms Bedué and Fritzsche (2022) argument that perceived transparency is a core antecedent of trusting AI by helping users to have a meaningful understanding of how algorithmic decisions are being made. In this study, when candidates perceived the AI-enabled recruitment system as transparent, they formed positive attitudes, proving that explainability is a critical relational and functional role in shaping acceptance. Additionally, the result supports the findings of Felzmann et al. (2019), AbdulKareem et al. (2024), and Angerschmid et al. (2022), who underline that transparency—especially supplemented with context and communicated appropriately—provides users with more confidence when interacting with AI systems. The moderating role of AI experience aligns with AbdulKareem et al. (2024) observation that digital literacy strengthens the perception of transparency and the transparency–acceptability relationship.

Perceived fairness shown to significantly influence job candidates' attitudes toward AI-enabled recruitment, confirming the previous literature underlining fairness as a prominent determinant of user acceptance in high-stakes decision contexts.

This result supports Kim and Heo (2021) and Nørskov et al. (2019), who exhibited that even when AI systems are deemed fair, they critically shape users' convenience and engagement. Furthermore, it confirms Teodorescu et al. (2021) argument that socio-technical fairness requires context-aware of human-AI collaboration. The findings thus build on previous research by empirically demonstrating that fairness is not a mere secondary consideration but rather a fundamental antecedent of candidate acceptance, which is particularly relevant for developing labour markets where ethical legitimacy might be scrutinised more closely due to comparatively weaker institutional safeguards.

The mediation of trust between transparency and attitude validates that explainability and openness towards the AI are key trust-building means and profoundly ethical imperatives. Candidates hold more positive attitudes when they believe AI decisions are interpretable and comprehensible directly, and through increased trust. However, the trust did not mediate the perceived risk–attitude relationship, implying a more complex pathway. Risk appeared to have a direct negative influence on attitudes, yet there was no significant intervention for trust in this relationship. These findings may indicate that candidates' risk perceptions stem from structural concerns and systemic issues, such as data misuse or bias that cannot be overcome by solely trusting the system's competence. Previous literature (Araujo et al., 2020; Li, 2025) has also found that high-risk contexts dictate more than trust to overcome user scepticism.

Respondents' prior AI experience moderated the relationship between perceived transparency and perceived risk with their attitude toward AI-enabled recruitment. The positive influence of transparency on attitude was stronger among those with more experience interacting with AI, which implies that experienced users are keener on the explanations and justifications behind the decisions. This finding aligns with the literature demonstrating how digital proficiency magnifies user expectations of clarity and fairness of AI (AbdulKareem et al., 2024; Shin, 2021).

Likewise, the adverse effect of risk on attitude was lessened for users with increased AI experience, suggesting that familiarity with AI lowers suspicion and increases AI acceptance. This finding has practical implications where increased awareness, familiarity, and training interventions might alleviate the risk perceptions, at least for less experienced candidates.

In contrast, AI experience did not moderate the effects of perceived fairness and ease of use on attitude, as these dimensions are arguably inherently salient qualities of the technology. Candidates could consider fair treatment and user-friendly systems as universally high priorities, even without prior exposure to AI. These findings indicate that fairness is yet a first-order issue that cuts across technical competence.

The study helpfully addresses a broad gap in the literature by shifting focus from employer or system analysis toward candidate perceptions. It enriches conventional technology acceptance models by ingraining ethical and relational variables as core determinants of attitude and acceptance. Moreover, investigating the mediation role of trust strengthens its central role in aligning system features with user attitudes, which is a contribution to both AI trust and socio-technical literature.

The moderating role of experience adds a novel contextual layer. Furthermore, the nonsignificant influence of ease of use challenges traditional assumptions in TAM, suggesting that ethical concerns outweigh usability in evaluative contexts like recruitment.

Moreover, the outcomes support the calls for socio-technical models of AI acceptance (Glikson & Woolley, 2020; Wanner et al., 2022) that embrace the need to balance psychological, ethical, and contextual factors with technological efficiency. Trust, as proved here, is not an inherent characteristic but a function framed by the system characteristics and users' familiarity and experience.

The findings emphasise the importance of AI transparency and fairness for HR professionals and technology developers. Perception of fairness and decision-making clarity are vital to users' acceptance and trust. Organisations must embrace explainable AI interfaces and formulate exhaustive policies to ensure procedural fairness. The findings underscore the importance of educating candidates about AI tools and enforcing familiarity within the process. To build a sounder understanding of AI-enabled tools, increasing trust and lowering negative risk perceptions, digital orientation sessions or interactive explainers could be utilised to give inexperienced applicants.

Since attitude and trust are found to be strongly correlated, hiring processes should include trust-building strategies, such as human oversight, transparent scoring rubrics, or ethical assurances. Not only do these actions enhance acceptance, but they also promote organisational legitimacy and reputation.

Conclusions

This study contributes to understanding AI-enabled recruitment acceptance from job candidates' perspectives in an emerging market context, such as Jordan. Specifically, it investigates the role of their fairness, transparency, risk, trust, usefulness, and ease of use perceptions while considering their prior AI experience as a moderator. Grounded on preceding technology adoption (TAM, UTAUT, and the FATE framework) as a theoretical foundation, the study incorporated essential ethical and psychological dimensions into a candidate-centric framework by integrating context-specific ethical and experiential dimensions relevant to the HR recruitment context. The findings offer theoretical insights and practical implications for the responsible and inclusive usage of AI in processing hiring decisions.

The findings revealed that AI trust, perceived fairness, usefulness, and transparency significantly affect shaping candidate attitudes toward AI-enabled recruitment. On the other hand, ease of use and risk perception had no substantial direct effect, implying that respondents placed greater importance on AI ethical and relational characteristics over technical functionality.

Additionally, the significant mediation role of trust between fairness, transparency, and attitude confirms its role as a bridge between ethical system characteristics and acceptance. The moderating role of AI-experience on the effects of transparency and risk emphasises the importance of familiarity in shaping receptiveness to AI.

These findings underline the necessity of producing AI systems that are functionally efficient but also fair, transparent, and trustworthy. As AI continues to reshape HRM practices, organisations should not wait passively until AI video interviews are common practice; instead, proactively address user concerns in the early stages of such HRM implementations, especially among external users such as job applicants who have no direct control over or adequate awareness of the used algorithms.

By grounding these recommendations in the Jordanian context of high youth unemployment and low levels of trust among the public for automated decision-making, this study contributes to context-specific insights which is often missing in Western-centric AI research. It supports the goals of SDG 8 ("Decent Work and Economic Growth"), specifically target 8.5, which advocates for fair and inclusive hiring practices.

In conclusion, as AI transforms the way HRM work is done around the globe, organisations need to consider building trust, fairness, and transparency, especially when leveraging AI tools that connect external stakeholders such as job candidates. The study advocates that when it comes to AI and automation, moving away from a technologically deterministic approach toward developing human-centred, trust-aware frameworks to facilitate responsible AI adoption.

Although the study offers valuable input to the technology adoption and acceptance literature by investigating candidates' attitudes toward AI-enabled recruitment, several limitations must be acknowledged. Firstly, it is limited to the Jordanian pharmaceutical sector while targeting limited preselected job vacancies at entry to mid-level careers. As such, this industry-specific and regional frame may constrain the generalizability to other sectors, labour markets and cultures with distinctive technological infrastructure, job applicants' expectations, or social norms.

Additionally, employing a cross-sectional design that captures perceptions at a specific point in time does not consider the potential shifts in attitude during the recruitment process that might happen after repeated exposure to AI-enabled systems. Longitudinal studies are recommended as they yield an improved understanding of trust, resistance, and perceptions evolution through the employment process up to receiving the final employment decision.

Although self-reported data, such as questionnaire-based methods, are well-suited to measure perceptions, they may be prone to social desirability bias or limited knowledge of the underlying functionality. Future research that comprises experimental simulations, behavioural data, or system logs is recommended to triangulate how candidates react to algorithmic real-time decisions.

The study considered only a single moderating variable, respondents' experience with AI. Although it proved insightful, Further research might consider broadening the investigation to incorporate other potential moderators such as perceptions of justice in the organisation, personality traits, social pressure, digital literacy, and others.

Lastly, although attitude is argued to be the strongest predictor of acceptance and intention, this study did not examine the complete outcomes, such as respondents' continuation or withdrawal, organisational attractiveness, and recruitment process effectiveness. Future research that investigates the influence of perceptions on applicants' actual behaviour and decisions throughout and after the recruitment process.

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