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Ethical Perceptions of AI in Hiring and Organizational Trust: The Role of Performance Expectancy and Social Influence

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Abstract

The use of artificial intelligence (AI) in hiring entails vast ethical challenges. As such, using an ethical lens to study this phenomenon is to better understand whether and how AI matters in hiring. In this paper, we examine whether ethical perceptions of using AI in the hiring process influence individuals' trust in the organizations that use it. Building on the organizational trust model and the unified theory of acceptance and use of technology, we explore whether ethical perceptions are shaped by individual differences in performance expectancy and social influence and how they, in turn, impact organizational trust. We collected primary data from over 300 individuals who were either active job seekers or who had recent hiring experience to capture perceptions across the full range of hiring methods. Our findings indicate that performance expectancy, but not social influence, impacts the ethical perceptions of AI in hiring, which in turn influence organizational trust. Additional analyses indicate that these findings vary depending on the type of hiring methods AI is used for, as well as on whether participants are job seekers or individuals with hiring experience. Our study offers theoretical and practical implications for ethics in HRM and informs policy implementation about when and how to use AI in hiring methods, especially as it pertains to acting ethically and trustworthily.

Keywords

Ethical perceptions, Artificial intelligence , Hiring, Organizational trust, Performance expectancy, Social influence

Introduction

The ethics of artificial intelligence (AI) have been broadly considered for a generation, but interest in the topic has sharply risen in recent years (Ferrario et al., 2020; Glikson & Woolley, 2020; Lockey et al., 2021) as AI has transitioned from an exploratory stage to mainstream reality. AI refers to machine-based systems which collect information and make decisions autonomously, mimicking human intelligence (OECD, 2019; Siau & Wang, 2018). Applications of such tools include machine learning, voice recognition, visual perception, and natural language processing abilities (Sohn & Kwon, 2020; Zhang & Lu, 2021) such as those required to hold a phone or chatbot dialogue. AI tools differ from other innovative IT products in that they are built with intelligence to act autonomously based on information they collect and process from interactions with their environment (Gonzalez-Garcia et al., 2017). Accordingly, the ethics of AI have been explored across contexts to study the displacement of human workers (Brynjolfsson & McAfee, 2014) and algorithmic discrimination (Lambrecht & Tucker, 2019), and in critical settings such as elderly care (Robinson et al., 2013), medical diagnosis (Choi et al., 2016), and more recently in job recruitment (Tambe et al., 2019).

At its core, AI has the potential to optimize and objectivize the hiring process (Polli, 2019), potentially serving all stakeholders. Nonetheless, stakeholder tensions about the legal and ethical implications of using AI in the con- text of hiring are emerging, especially as their various features, such as privacy protections, are inevitably compared to existing scientifically based methods used for decades (Dattner et al., 2019). On the one hand, hiring managers using AI seek efficiency and accuracy (IBM, 2018a; Peck, 2013) to identify the best candidate-job matches, a task at which AI succeeds by identifying behavioral patterns that were previously inaccessible to HR managers (Chamorro- Premuzic et al., 2019; Upadhyay & Khandelwal, 2018). On the other hand, job seekers want fairness (Lee, 2018), equal opportunity (Speicher et al., 2018), and unbiased and transparent processes (Jasanoff, 2016; Shilton et al., 2013) that protect their personal and sensitive demographic data, including political affiliation, sexual orientation, and mental or emotional health status (Dattner et al., 2019). While the popular press has highlighted the tensions around these issues (Chamorro-Premuzic et al., 2019), there has been fragmented scholarly attention to the perceived ethics of AI during the hiring process

(Leicht-Deobald et al., 2019; Nikolaou et al., 2019), especially from the applicant's perspective (Laurim et al., 2021; Nawaz, 2019).

The limited research on ethical perceptions of AI in hiring may be the result of two important limitations in how AI is typically treated in the Human Resource Management (HRM) literature. First, most of this work has focused either on the question of whether such practices are fair (e.g., van den Broek et al., 2019) and on how human trust in the various forms of AI (robot, virtual, embedded) develops (Glik- son & Woolley, 2020). In contrast, far less work has focused on how AI itself impacts individual ethical perceptions and the degree to which we trust the organizations that use it.

For instance, Tambe et al. (2019) discuss at length the various reasons why AI is problematic within the realm of HRM but leave unaddressed the issue of how AI impacts our ethical perceptions. Similarly, Glikson and Woolley (2020) highlight that human trust in AI is influenced by AI's innate characteristics such as tangibility (Chattaraman et al., 2014), task performance (Ramchurn et al., 2016), and reliability (Fan et al., 2008), but provide only hints of how the usage of AI influences trust in the organizations that use it. Increasingly, business ethics scholars explicitly call for future research to explore perceptions of ethical decision-making (Jagger et al., 2016) and specifically on how applications of AI are integrated within organizations (see Haenlein et al., 2022). Thus, we know much more about why we trust AI than we do about why we trust the organizations that use it. This is a critical question with ethical implications, arguably more important than understanding why we approve of AI. In this paper, we respond to numerous calls to examine the ethical perceptions of the use of AI (e.g., Munoko et al., 2020) in the context of HRM, a rapidly evolving research area which offers distinct ethical challenges (Tambe et al., 2019). We propose that a critical concern regarding AI applications is the impact of individual ethical perceptions towards the organizations behind the technologies. Rather than directing our attention to the robots and algorithms, whose designs are often inaccessible to the public due to property rights, we posit that it is important to reflect on whether we trust the organizations that use them. As such, we build on organizational trust research (e.g., Greenwood & Van Buren III, 2010; Lin, 2010; Schoorman et al., 2007) to propose that ethical perceptions about the use of AI in hiring are likely to influence one's perceptions of whether the organization using AI is trustworthy.

A second important limitation emanating from prior research is that whether AI practices in hiring are perceived as being ethical is likely to vary (Tambe et al., 2019). First, some people may believe that AI is going to control their work, whereas others perceive that AI can make their work more efficient (Brynjolfsson & McAfee, 2014; Howard, 2019). Suitably, we seek to understand how ethical perceptions of AI use in hiring vary depending on individual differences of performance expectancy (Brynjolfsson & McAfee, 2014; Brynjolfsson et al., 2019). Second, we explore whether individuals' reliance on other people's views influence their ethical perceptions about the acceptability of AI (Laurim et al., 2021).

In this paper, we build on the unified theory of acceptance and use of technology (UTAUT; Venkatesh et al., 2003) to examine whether and how both performance expectancy and social influence are related to individuals' ethical perceptions about the use of AI in hiring. While various technology acceptance models have been studied over time, the UTAUT is recognized as the most robust and widely validated frame- work across contexts (Oshlyansky et al., 2007; Venkatesh et al., 2012, 2016), capable of adapting to any sort of emerging technology, while explaining almost seventy percent of variance in technology acceptance (Davis et al., 1989; Venkatesh et al., 2003).

The overarching purpose of this paper is thus to explore how perceptions about the ethics of AI in hiring are related to the extent to which individuals trust the organizations that use it, and how these ethical perceptions are shaped by individual differences in performance expectancy and social influence. As this paper is one of the first to tackle these issues and has an exploratory element, we, by design, consider various types of AI (e.g., augmenting, autonomous) and all phases of the hiring process (e.g., outreach, screening, assessment and selection, facilitation) (Hunkenschroer & Luetge, 2022). We collected data from over 300 individuals who were either active job seekers or who had recent hiring experience to capture perceptions across the full range of methods (McCarthy et al., 2017; Ryan & Ployhart, 2000). Overall, we find that performance expectancy, but not social influence, influences the ethical perceptions of AI in hiring, which in turn influence perceptions of organizational trust.

This paper's contributions to the ethics and HRM literatures, and the growing literature on AI are threefold. First, we build on the UTAUT (Venkatesh et al., 2003) to examine whether and how expectations about AI's performance and social influence during the hiring process are likely to influence both job seekers and individuals with hiring experience's ethical perceptions about the use of AI in hiring. Second, we extend the organizational trust model (Schoorman et al., 2007) to the study of ethical perceptions of AI in hiring. Specifically, while trust and ethics have often been studied together (e.g., Greenwood & Van Buren III, 2010), we seek to further our understanding of whether and how ethical perceptions of AI use in hiring are likely to influence organizational trust. Finally, this study also has implications for HRM practices. Our findings seek to inform HRM departments and managers on policy implementation about when and how to use AI in hiring methods, especially as it pertains to acting ethically and trustworthily.

Theoretical Framework

Artificial Intelligence in Hiring

Artificial intelligence refers to the ability of computer systems to execute tasks autonomously, mimicking human intelligence (OECD, 2019; OED, 2021). Its application to the various decision-making stages of the hiring process (e.g., outreach, screening, assessment and selection) is becoming increasingly widespread (Leicht-Deobald et al., 2019). In fact, over half of human resource (HR) managers identify AI as a time-saving tool by the year 2022 (CareerBuilder, 2017). Indeed, AI can leverage algorithms to formulate job ads, carry out targeted advertisement, and identify active and passive candidates during the outreach phase; it can also scan resumes and rank candidates during the screening phase; further, it can use face and voice recognition and linguistic analysis to analyze video interviews and writing samples, all the while testing for skills, capabilities, and psychological profiles during the assessment and selection phase (for a full review see Hunkenschroer & Luetge, 2022).

At its core, AI offers the capability to analyze vast amounts of unstructured data—numerical, textual, video— and provide precise results very quickly (Munoko et al., 2020) using consistent criteria (Why, 2018). Further, AI can also facilitate the hiring process by communicating with applicants to answer questions about the process or schedule interviews

(Rąb-Kettler & Lehnervp, 2019), and even send out job offers (Sanchez-Monedero et al., 2020). As of January 2020, there were at least 11 firms that offer algorithmic pre-screening assessments that had raised between $1 MM and $93 MM in investment capital in the USA and 2020). Companies like IBM and Xerox Services advertise AI-enabled hiring tools citing higher efficiency (IBM, 2018a) and accuracy to identify person-job fit (Peck, 2013), granting AI a superior status against alternate methods riddled with biased human intuition and error (Leicht-Deobald et al., 2019).

The adoption of AI in hiring seems to benefit from a general optimism that AI is highly effective across all domains, or soon will be. A recent survey conducted by Zhang and Dafoe (2019) finds that the U.S. public places the likelihood of high-level machine intelligence[1] at 54% within ten years. In practice, there is evidence that AI is developing at a faster rate than we can control (BBC, 2018). In contrast, however, AI experts place the timeline for strong AI, capable of exceeding human performance, at about 50 years out (Grace et al., 2018). Overall, AI-enabled tools can be perceived by the public as emancipatory—proficient at democratizing processes that free humans (Du, 2021) from the labor-intensive tasks in hiring. Indeed, research shows that individuals are prone to allow the promise of technology to outpace reality, becoming over-optimistic about the potential of AI-enabled tools without sufficient empirical evidence (Clark et al., 2016). Nonetheless, there is rising concern of whether AI-enabled tools in hiring are ethical (Tambe et al., 2019).

The Ethics of Artificial Intelligence in Hiring

The rise of technology seems to have emboldened the relinquishment of responsibility (Johnson, 2015) with management leaders at times holding AI immune to ethical concerns (Gunz & Thorne, 2020). Thus, "who is accountable for the decision outcomes of machines?" Is

[1] "We have high-level machine intelligence when machines are able to perform almost all tasks that are economically relevant today better than the median human (today) at each task." (Zhang and Dafoe, 2019, p. 34).

the programmer who writes the algorithm ethically responsible? Or is it the organization using the technology the one responsible for identifying and resolving complex ethical dilemmas? (Gunz & Thorne, 2020, p. 155). This conundrum raises ethical implications in hiring given its "potential to change, shape, redirect and fundamentally alter the course of other people's lives" (Margolis et al., 2007, p. 237), in some cases leading to unemployment or underemployment (Du, 2021).

Contemporary decision-making in various business fields is increasingly delegated to AI systems, fueled by objectivity claims, market needs for rapid assessment of large applicant pools, and by over-optimism about its efficacy (Araujo et al., 2020). This rapid rollout further complicates ethical concerns about its effects (Wright & Schultz, 2018) and the risk Canada alone (Raghavan et al., 2020). These vendors offer services that analyze images, videos, gameplay, application documents, and other materials to assess cultural fit, predict sales, and measure skill competencies (Raghavan et al., of inappropriate AI control or dominance in HRM (Leclercq-Vandelannoitte, 2017; Leicht-Deobald et al., 2019). Perhaps the most widely known example of this risk is Amazon's 2014 faulty AI hiring tool application, which promised to become the most accurate tool for identifying top candidates, but was recalled a year later for following a pattern that discriminated against women for its most technical job openings (Dastin, 2018).

Adopters of AI-enabled tools generally assume these systems are objective (Parry et al., 2016), accurate, and that any deviance from the desired boundaries is detectable and correctable (Munoko et al., 2020). However, the capability of computers to perform cognitive tasks previously undertaken by humans is encoded and calibrated by a human programmer, who may knowingly or unintentionally extend their value judgments (Jasanoff, 2016) and ideological bias into the design (Shilton et al., 2013). In fact, recent evidence in HRM shows that the automated decision-making of AI can have adverse practical consequences for humans (Martin et al., 2019), creating dependency and possibly alienation (Du, 2021). A recent IBM study of AI systems identified inherent discriminatory biases in algorithms which alienated users based on individual characteristics, even disqualifying competent candidates from employment (IBM, 2018b). Other evidence finds that "data science techniques perform poorly when predicting rare [new] outcomes", raising ethical concerns about the fairness of outcomes that deviate from preceding HR decision paths (Tambe et al., 2019, p. 16).

The ethical challenge behind the promise of AI in the hiring process resides, in part, in the lack of accessibility to the proprietary code behind AI-enabled tools, which firms own and control (Pasquale, 2015). This separation makes it difficult to detect HR ethical risks prior to its application in human contexts (Leicht-Deobald et al., 2019). Further- more, the algorithms that form these proprietary codes are designed to follow archival employment trends, thus perpetuating faulty racial, gender, and other forms of human discrimination (for examples see Barocas & Selbst, 2016; Buolamwini & Gebru, 2018; Martin, 2019; Noble, 2018; O'Neil, 2016). The lack of control that HR managers hold over the inherent design of the AI-enabled tools they use in the hiring process reinforces the importance of investigating how individuals perceive the organizations that use AI and whether they consider them trustworthy.

Ethical Perceptions of AI in Hiring and Organizational Trust

Trust entails an expectation of morally proper behavior (Greenwood & Van Buren III, 2010). The trust referent can be an individual or an organization (Currall & Inkpen, 2002; Zaheer et al., 1998). In this paper, we investigate how perceptions about the ethics of AI in hiring affect the extent to which job seekers and individuals with hiring experience view the organization using AI as being trustworthy. Indeed, trust is at the center of much of the current discourse around AI applications (Martin et al., 2019), mainly in connection to perceptions of fairness in hiring decisions (Lee, 2018). The alleged higher accuracy and objectivity that AI grants "may evoke blind trust in processes and rules, which may ultimately marginalize human sense-making as part of the decision-making processes" (Leicht-Deobald et al., 2019, p. 378).

Although there are various approaches to understanding trust in business contexts (Pirson et al., 2019), for AI in hiring trust ensues when users in HR contexts perceive fairness in how AI reaches its decisions (Bloomberg, 2018). Even in situations when the AI process is too complex to fully understand, an organization may be deemed trustworthy if the AI outcomes are perceived as not only effective but also as supporting the user's interests (Martin et al., 2019). For instance, a survey on digital trust found that users are likely to trust an organization if they perceive that the organization is behaving ethically by safeguarding the users' records

(Accenture, 2015). Accordingly, individuals' ethical perceptions of AI in hiring can lead to organizational trust, which is widely accepted as a critical factor for organizational performance (Davis et al., 2000) and sustained success (Pirson & Malhotra, 2011).

Factors that Influence Perceptions of Technology and the Organizations that Use It

The rationale behind why we accept and use technologies such as AI has been studied extensively for over 40 years. The most robust and widely used framework is the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003). The UTAUT is the result of a rigorous synthesis of various elements from eight existing models of technology acceptance, including the Technology Acceptance Model (Davis, 1989), the Theory of Reasoned Action (Fishbein & Ajzen, 1977), and the Innovation Diffusion Theory (Rogers, 1995), each of which explains between 17 and 53 percent of variance in technology acceptance. The UTAUT, which subsumes these models, outperforms them all and explains 69 percent of such variance (Venkatesh et al., 2003). The UTAUT has since been validated many times (see Venkatesh et al., 2012), including across cultures (Oshlyansky et al., 2007).

Moreover, while some of the various acceptance models were developed with narrow contexts in mind such as just information systems (Davis, 1989) or personal computers (Thompson et al., 1991), others, including the UTAUT, are well adapted to any sort of emerging technology. This is important for our study because AI is a general-purpose technology that spans contexts and industries (Zhang & Lu, 2021).

While trust in an organization is different than trust in another individual, linking individual perceptions to group trust is an appropriate level of analysis (Currall & Inkpen, 2002) because trust always originates from individual perceptions, even when the trust referent is an organization (Currall & Inkpen, 2002; Zaheer et al., 1998). Implicit in the UTAUT, and its various extensions, is that acceptance of technology is the result of both individual cognitive and social processes. Thus, we borrow two antecedents from the UTAUT that are likely to impact individual ethical perceptions and lead to trust in the organizations that use AI, performance expectancy and social influence (Venkatesh et al., 2003).

Performance Expectancy of AI and Trust in the Organizations that Use It

Organizations that use effective methods are often more highly trusted (Gill et al., 2005; Mayer et al., 1995). Across the various AI tools currently under use, some work well (e.g., Gibney, 2016; Levy, 2009; Liao, 2020), whereas others fail quite completely (Knight, 2016; Yampolskiy, 2019). The relationship between performance and trust (i.e., in a brand or an organization) (Loureiro et al., 2018) is well established within the trust literature and is often referred to an agent's *ability* to undertake and complete vital tasks (Mayer et al., 1995). Further, the notion of ability specifically includes both technical (Greenwood & Van Buren III, 2010) and managerial competencies (Madhavan & Grover, 1998), in addition to practical functionality (Sheppard & Sherman, 1998). Several studies find that external stake- holders, such as suppliers, customers, and job seekers, are especially attuned to technical competency when it comes to trusting an organization (Morgan & Hunt, 1994; Parmigiani & Mitchell, 2005), and are more likely to be impacted by it (Pirson & Malhotra, 2011).

Although prior evidence suggests that technology performance expectancy (PE) indirectly influences trust, it is not yet clear how it occurs (Loureiro et al., 2018). In this study, we suggest that the relationship between performance expectancy and trust in an organization operates, at least in part, via ethical perceptions as a mediating influence. We arrive at this proposition as follows.

Venkatesh et al., (2012, p. 159) define PE as "the degree to which using a technology provides benefits to the consumers in performing certain activities". Thus, both ability and PE refer to the task effectiveness or technical competence of a technology (Schwoerer et al., 2005; Sheppard & Sherman, 1998). Whether a technology performs its function well or not has an impact on attitudes towards the technology (e.g., Gupta et al., 2021) and ethical perceptions (Brooksbank et al., 2019). For example, a recent study finds that when customers' performance expectations are met, they experience a form of psychological attachment (Marin et al., 2009) that manifests in positive attitudes, such as considering the technology as ethical.

We note here that the definition of PE allows for a subjective view of what "effectiveness" means, depending on what the desired benefits of a technology are for the individual. We know, for instance, that hiring managers seek AI for time-saving efficiency and accurate predictions of future job performance (IBM, 2018a; Peck, 2013), tasks at which AI is well suited

(Chamorro-Premuzic et al., 2019; Upadhyay & Khandelwal, 2018). In contrast, job seekers want fairness (Lee, 2018), equal opportunity (Speicher et al., 2018), and unbiased and transparent processes (Jasanoff, 2016; Shilton et al., 2013) that protect their personal and sensitive demographic data, including political affiliation, sexual orientation, and mental or emotional health status (Dattner et al., 2019).

Furthermore, evidence suggests that when stakeholders, such as customers and employees perceive company practices, such as technology adoption, to be ethical, this judgment eventually translates into trust in the organizations that use it. For example, Fatma and Rahman (2017) find that when hotel customers perceive hotel practices to be ethical, they also have greater trust and loyalty towards the hotel. This is especially true when stakeholders determine that organizational practices align with their personal values, leading to trust (Keh & Xie, 2009). The relationship between ethics and trust operates not only at a company level, but also at a brand and even a product level (Singh et al., 2012). This accords well with longstanding trust models. Implicit in all models of trust is the notion of the trust referent (an individual or organization) as a moral actor. We trust the referent because they have integrity, ability, and benevolence (Mayer et al., 1995). They act in our best interest even after we make ourselves vulnerable to them. In sum, we trust organizations that do ethical things. And conversely, we do not trust organizations that engage in practices we deem unethical. We thus hypothesize:

Hypothesis 1 The belief that AI is highly effective leads to greater trust in the organizations that use it. The effect is indirect and operates via increased ethical perceptions of AI.

Social Influence of AI and Trust in the Organizations that Use It

Organizations that use socially acceptable methods are also more likely to be trusted (Li et al., 2012). Unsurprisingly, not all forms of AI are equally acceptable to individuals or society at large (Kaplan, 2004). For instance, AI-driven robotics that perform assembly tasks in automobile factories (Müller-Abdelrazeq et al., 2019) are much more accepted than Amazon's AI recruiting tool designed to select the best job candidates (Dastin, 2018; Meyer, 2018). The likelihood and degree of acceptance thus depend on individual perceptions (Siau & Wang, 2018) and on the technology and its context. Fortunately, the UTAUT explains that social influence predicts acceptance and use of technology (Davis et al., 1989; Venkatesh et al., 2012). Our focus here is on social influences of AI acceptance as an antecedent of organizational trust, that, we hypothesize, operates through individual ethical perceptions.

Individuals frequently rely on social factors, such as the opinions of friends and cultural norms, to determine what they deem to be acceptable (Bozan et al., 2016). *Social influence* is the degree to which individuals are impacted by the beliefs of the key people in their lives, such as friends and family, about technology use (Kijsanayotin et al., 2009). Acceptance can emerge via various social mechanisms. Coercive pressure from authority figures, such as physicians and supervisors, can lead to acceptance of a technology (Bozan et al., 2016). Knowledge that usage of a technology is a generally accepted norm can also lead to acceptance (Jan et al., 2012; Liang et al., 2007; Teo et al., 2003). Finally, mimetic pressure, where positive outcomes such as greater respect are the observable results of technology usage, can also lead individuals to accept the technology themselves (Liu et al., 2010).

While there are many reasons technologies gain social acceptance, we note that acceptance is not the same as acceptability (Adell et al., 2018), or ethical approval. In other words, the practical acceptance of a thing is not equivalent to a normative moral designation of a thing as ethical (Hume, 2000). However, the two are linked (Van de Poel, 2016). For example, the wide-reflective-equilibrium model (Rawls, 2001) describes the process of individual resolves of what is moral as a reflective process where a wide net is cast that considers various moral frameworks. In practical terms, even though people come to distinct conclusions about ethics, when something is widely accepted, it is interpreted as a strong cue that most moral frameworks approve of it (Daniels, 1979). In simpler terms, coherence in public reason often leads to individual approval (Surowiecki, 2005).

In our context of interest, this means that as participants in the hiring process deem AI practices to be ethical due to the social influences of their personal network, the end result is that they then extend the favorable perceptions to the organizations that use those practices (e.g., Singh et al., 2012). As highlighted previously, virtually all trust theories describe trust referents (individuals or organizations) as moral actors that 'do what they ought to.' Job seekers, for instance, are likely to trust organizations that use AI if they perceive those practices to be compatible with notions of integrity and effectiveness (Mayer et al., 1995). In summary, we trust organizations that engage in practices approved by our social network. And conversely, we are less likely to trust organizations that engage in practices that our social network does not approve.

Hypothesis 2 The belief that AI is socially acceptable leads to greater trust in the organizations that use it. The effect is indirect and operates via increased ethical perceptions of AI.

Method

Sample and Procedure

We recruited participants using the platform Prolific Academic (www.prolific.co). Prior studies show that Prolific is a source of high-quality survey data (Palan & Schitter, 2018; Tilcsik, 2021). Compared to other survey platforms, data from Prolific shows a high level of internal reliability on psychometric scales, a low failure rate on attention checks, a high level of reproducibility of previously known effects, and low degrees of dishonest responding by participants (Peer et al., 2017). Notwithstanding, we took several measures to ensure the quality of the responses. First, we selected participants who had a completion rate above 95%, which corresponds not only to them finishing previous surveys, but also to getting rewarded for their participation. Second, we included attention checks in the survey to eliminate random responding. Finally, one of the authors double-checked the responses at the extremes (i.e., in terms of completion time) to further eliminate random responding. Specifically, since we were interested in studying ethical perceptions of hiring methods, we recruited 305 participants, among which 50% were actively job seeking, and 50% were employed and had hiring experience. Table 1 offers demographics and characteristics of the sample.

Participants were given a link to a web-based survey. After reading a cover sheet and agreeing to participate, we provided them with a definition of AI followed by a script (see survey instrument in “Appendix” for definition and script). After carefully reading the script, participants responded to several items related to their ethical perceptions about various hiring methods used by the company, along with feelings about the company (i.e., organizational trust). Participants then answered questions related to their performance expectancy and social influence, before answering some demographic characteristics at the end of the survey.

Table 1 Demographics and characteristics of sample

Demographics		% (*N*=100)
Country		
	US	11.8
	UK	78.6
	Ireland	1.3
	Canada	8.3
Gender		
	Male	41
	Female	59
Age		
	18-25	25.2
	26-35	30.5
	36-45	23.9
	46-55	12.5
	56-65	7.9
Highest education		
	High School	10.2
	Some college	25.6
	College degree	41.3
	Post-graduate degree	22.9
Job seeker		
	Yes	50.2
	No	49.8
Hiring Experience		
	None at all	50.2
	A little	12.5
	A moderate amount	20.6
	A lot	10.5
	A great deal	6.2

Measures

Hiring Methods

We developed a list of hiring methods specifically for this study. Because trust in AI is influenced by the task being performed (Gaudiello et al, 2016; Logg et al., 2019; Ram- churn et al., 2016), we generated a list of tasks across critical stages of the entire hiring process. We consulted both practical (e.g., Bauer et al., 2012; Pulakos, 2005) and scientific sources (e.g., McCarthy et al., 2017; Ryan & Ployhart, 2000) to build this list. We included the following ten hiring methods from more traditional to more innovative methods: “screening applicants to determine whether they meet the minimum job qualifications,” “assessing applicants’ characteristics and traits such as intelligence, honesty, and personality,” “conduct applicant interviews,” “select which applicants will be hired,” “analyze submitted documents from applicants,” “analyze social media information for traits and characteristics,” “analyze interview text for answer quality,” “analyze video of applicants for nonverbal behaviors,” “analyze still images of applicants for facial features,” and “analyze audio of applicants for voice cues.” We included the methods after the script asking participants to “Indicate the degree to which you consider the use of AI to be an ethical practice during each of the following stages of the recruiting process.” Participants responded on a five-point scale (1 = very unethical; 5 = very ethical).

Table 2 Factor loadings for hiring methods based on a principal components analysis

	Archival hiring methods	Hurdle-process hiring methods	Intrusive hiring methods
Screening applicants to determine whether they meet the minimum job qualifications	0.810*	0.286	-0.064
Assessing applicants’ characteristics and traits such as intelligence, honesty, and personality	0.396	0.720*	0.187
Conduct applicant interviews	0.228	0.904*	0.073
Select which applicants will be hired	0.199	0.891*	0.095
Analyze social media information for traits and characteristics	0.375	-0.167	0.641*
Analyze interview text (transcribed) for answer quality	0.555*	0.349	0.444*
Analyze video of applicants for nonverbal behaviors	0.240	0.231	0.768*
Analyze still images of applicants for facial features	-0.062	0.043	0.849*
Analyze audio of applicants for voice cues	0.046	0.238	0.841*
Analyze submitted documents from applicants	0.707*	0.349	0.279

Items with asterisk indicate factor into which they load

We conducted an Exploratory Factor Analysis (EFA) to explore whether the methods loaded onto one or multiple factors. Specifically, we used Principal Components Analysis (PCA) with varimax rotation to identify and compute composite scores for the factors underlying our ten hiring methods. As indicated in Table 2, we found that the ten methods loaded onto three distinct factors (i.e., with eigen- value greater than one), which we coined “archival” hiring methods (i.e., those based on submitted materials and documents), “hurdle-process” hiring methods (i.e., those based on the multiple hurdle model of hiring), and “intrusive” hiring methods (i.e., those methods more invasive to privacy). Three methods loaded onto the “archival” factor, with loadings from 0.56 to 0.81. Three methods loaded onto the “hurdle-process” factor, with loadings from 0.72 to 0.90. The four remaining methods loaded onto the “intrusive” fac- tor, with loadings from 0.64 to 0.85. All factor loadings were above the recommended cut-off (i.e., factor loadings ≥ 0.40; Hinkin, 1998). The three factors combined explained 73% of the variance. Reliability coefficients (Cronbach’s alphas) are 0.70 for the archival factor, 0.74 for the hurdle-process factor, and 0.84 for the intrusive factor.

While we built on prior research to create the hiring methods items for this study, we collected additional data to examine the factor structure of our measure with a Confirmatory Factor Analysis (CFA) using STATA 16.1 (Stata- Corp, 2019), and to thus provide further validation for our measure. To do so, we collected a second sample from Prolific, similar to our original sample (N = 281, average age 36.3, 63.7% female), in which we presented participants with the definition of AI, followed by the same scenario as above, and then asked for their ethical perceptions about the ten hiring methods. To ensure proper structure, the λ values for all items should be both large ($\lambda \geq 0.30$) and significant ($p < 0.05$) (Hair et al., 1998). In support of the three-factor structure identified in the study sample, results of the CFAs indicated that λ values ranged from 0.65 to 0.83 for the three items of the archival factor, from 0.73 to 0.87 for the three items of the hurdle-process factor, and from 0.66 to 0.91 for the four items of the intrusive factor. All values exceeded the recommended 0.30 cut-off, while significantly loading onto each factor ($p < 0.01$).

Then, as recommended by Hu and Bentler (1999), we examined how well our hypothesized three-factor structure fit our data, using the chi-square goodness of fit test, the comparative fit index (CFI), the Tucker-Lewis index (TLI), the root-mean-square error of approximation (RMSEA), and the standardized root mean square residual (SRMR). We found that the three-factor structure provided an accept- able fit to the data (χ^2 (32, N = 281) = 131.82, CFI = 0.94, TLI = 0.91, RMSEA = 0.106, SRMR = 0.062). Importantly, we found that the three-factor structure provided a significantly better fit than a one-factor structure with all items loading onto the same factor (χ^2 change = 220.53 with 3 Δdf, $p < 0.01$). Results from the CFA analyses provided further validation for our three-factor hiring methods structure.

Organizational Trust

We measured organizational trust with a five-item scale from Biswas and Suar (2016). Sample items included “Employees’ perception of employer having high integrity” and “Employees’ perception of employer being honest and truthful.” Participants responded on a five-point scale (1 = strongly disagree; 5 = strongly agree). The reliability coefficient for this scale was 0.89.

Performance Expectancy

We assessed performance expectancy using three items adapted from Venkatesh et al. (2012)’s UTAUT. The items were “I find AI useful in my daily life,” “Using AI helps me accomplish things more quickly,” and “Using AI increases my productivity.” Respondents answered on a five-point scale (1 = strongly disagree; 5 = strongly agree). The reli- ability coefficient for this scale was 0.93.

Social Influence

We measured social influence using three items adapted from Venkatesh et al. (2012)’s UTAUT. The items were “People who are important to me think that I should use AI,” “People who influence my behavior think that I should use AI,” and “People whose opinions that I value prefer that I use AI.” Respondents answered on a five-point scale (1 = strongly disagree; 5 = strongly agree). The reliability coefficient for this scale was 0.93.

Control Variables

Following the literature, we suspected respondents would vary in their ethical perceptions of AI depending on demo- graphic characteristics, such as gender, age, and education (see Laurim et al., 2021). Thus, we controlled for these demographic characteristics, which are considered sensitive ethical features in human interactions with autonomous technology (Hermann, 2021; North-Samardzic, 2020; Speicher et al., 2018). In addition, we controlled for experience, another relevant factor that affects individual judgement (Venkatesh et al., 2003); specifically, we controlled for whether the respondent was an active job seeker, and whether they had hiring experience, because these factors can potentially influence individual ethical perceptions about the use of technology in hiring (Anderson, 2003). Specifically, participants reported their *gender* (0—female; 1— male), their *highest education* (1—less than high school; 2—high school; 3—some college; 4—college degree; 5—post-graduate degree), and whether they were *actively searching for employment* (0—yes; 1—no). Finally, we also asked participants to report, using a five-point scale (1 = none at all; 5 = a great deal) the extent to which they have *experience hiring* employees.

Table 3 Means, standard deviations, and correlations

Variables	*M*	*SD*	1	2	3	4	5	6	7	8
1 Organizational trust	2.99	0.88	***0.89***							
2 AI in hiring methods	2.67	0.79	0.56*	***0.87***						
3 Performance expectancy	3.21	1.10	0.27*	0.43*	***0.93***					
4 Social influence	2.50	1.00	0.21*	0.35*	0.63*	***0.93***				
5 Gender	0.41	0.49	0.04	0.01	0.02	0.08	–			
6 Age	35.60	12.29	– 0.12*	– 0.06	– 0.15*	– 0.08	0.02	–		
7 Highest education	3.77	0.92	– 0.01	0.01	0.05	0.00	– 0.07	0.10	–	
8 Job seeker	0.50	0.50	– 0.05	0.05	– 0.06	0.03	– 0.08	0.57*	0.02	–
9 Hiring experience	1.10	1.30	0.00	0.08	– 0.02	0.03	– 0.05	0.54*	0.05	0.85*

N = 305. **p* < 0.05. Reliability coefficients (Cronbach's alphas) appear along the diagonal in italic and bold. Gender is coded as 0 for female, and 1 for male. Highest education is coded 1 for less than high school, 2 for high school, 3 for some college, 4 for college degree, and 5 for post- graduate degree. Active job seeker is coded 0 for yes, 1 for no

Results

Table 3 presents the descriptive statistics and correlations among the variables. Examination of these correlations indicates that organizational trust was positively related to AI in hiring methods ($r = 0.56$, $p < 0.05$), performance expectancy ($r = 0.27$, $p < 0.05$), and social influence ($r = 0.21$, $p < 0.05$). Furthermore, AI in hiring methods was positively related to both performance expectancy ($r = 0.43$, $p < 0.05$) and social influence ($r = 0.35$, $p < 0.05$).

Measurement Model and Hypothesized Structural Model

The hypothesized model was tested using structural equation modeling with STATA 16.1 (StataCorp, 2019). Five indices were used to assess model fit: the chi-square goodness of fit test, the comparative fit index (CFI), the Tucker-Lewis index (TLI), the root-mean-square error of approximation (RMSEA), and the standardized root mean square residual (SRMR). Hu and Bentler (1999) have suggested cutoff criteria for the various fit indices. Specifically, for both the CFI and TLI, indices above 0.95 represent excellent fit, between 0.90 and 0.95 good fit, and below 0.90 poor fit. For the RMSEA, indices between 0.01 and 0.05 represent excellent fit, between 0.05 and 0.08 good fit, and above 0.08 poor fit. Finally, for SRMR, indices below 0.08 are generally considered good fit.

We found that the measurement model provided a good fit to the data (χ^2 (267, N = 305) = 440.16, CFI = 0.96, TLI = 0.95, RMSEA = 0.046, SRMR = 0.082). We also found that the hypothesized model provided an excellent fit to the data (χ^2 (267, N = 305) = 415.79, CFI = 0.96, TLI = 0.96, RMSEA = 0.043, SRMR = 0.046). The hypothesized model provided a significantly better fit than the measurement model (χ^2 change = 34.37 with 2 Δdf, $p < 0.01$).

Hypotheses Testing

Table 4 includes the results for the hypothesized structural model, including both direct and indirect hypothesized effects. Hypothesis 1, which proposed that a belief that AI is highly effective leads to greater trust in the organizations that use it, indirectly through increased ethical perceptions of the use of AI in hiring, was supported. As shown in Table 4, we found that performance expectancy was positively related to ethical perceptions of using AI in hiring (β = 0.41, p = 0.00), which in turn was positively related to organizational trust (β = 0.64, p = 0.00). Furthermore, we also found that performance expectancy was indirectly positively related to organizational trust (β = 0.18, p = 0.00).

Hypothesis 2, which proposed that the belief that AI is socially acceptable leads to greater trust in the organizations that use it, indirectly through increased ethical perceptions of the use of AI in hiring, was not supported. As shown in Table 4, we found that social influence was not related to ethical perceptions of using AI in hiring (β = 0.11, p = 0.18). Furthermore, while ethical perceptions of using AI in hiring was positively related to organizational trust, (β = 0.64, p = 0.00), the indirect relationship between social influence and organizational trust was not significant (β = 0.05, p = 0.19).

While we theorized indirect effects of performance expectancy and social influence on organizational trust, via ethical perceptions of the use of AI in hiring, we also tested an alternative model that included direct paths from both performance expectancy and social influence to organizational trust. We found that neither performance expectancy (β = − 0.05, p = 0.57) nor social influence (β = − 0.01, p = 0.94) was directly related to organizational trust. Further- more, the alternative model, including the two direct paths, did not provide a better fit to the data (χ^2 change = 0.81 with 2 Δdf, p = ns). Overall, we found support for the hypothesized structural model in Fig. 1, in that performance expectancy, but not social influence, was related to the ethical perceptions of using AI across various hiring methods, which in turn was related to organizational trust.

Table 4 Regression coefficients for structural equation model

Variables		Direct effects			Indirect effects		
		β	SE	*p*	β	SE	*p*
Organizational trust							
	AI hiring	0.64	0.05	0.00			
	Performance expectancy	-	-	-	0.18	0.04	0.00
	Social influence	-	-	-	0.05	0.04	0.19
	Gender	0.03	0.05	0.59			
	Age (log)	-0.03	0.07	0.67			
	Highest education	0.01	0.05	0.89			
	Job seeker	-0.12	0.10	0.25			
	Hiring experience	0.006	0.10	0.51			
AI in hiring							
	Performance expectancy	0.41	0.08	0.00			
	Social influence	0.11	0.09	0.18			
	Gender	-0.01	0.06	0.92			
	Age (log)	-0.10	0.07	0.18			
	Highest education	-0.02	0.06	0.78			
	Job seeker	0.00	0.12	0.99			
	Hiring experience	0.06	0.11	0.19			

N = 305

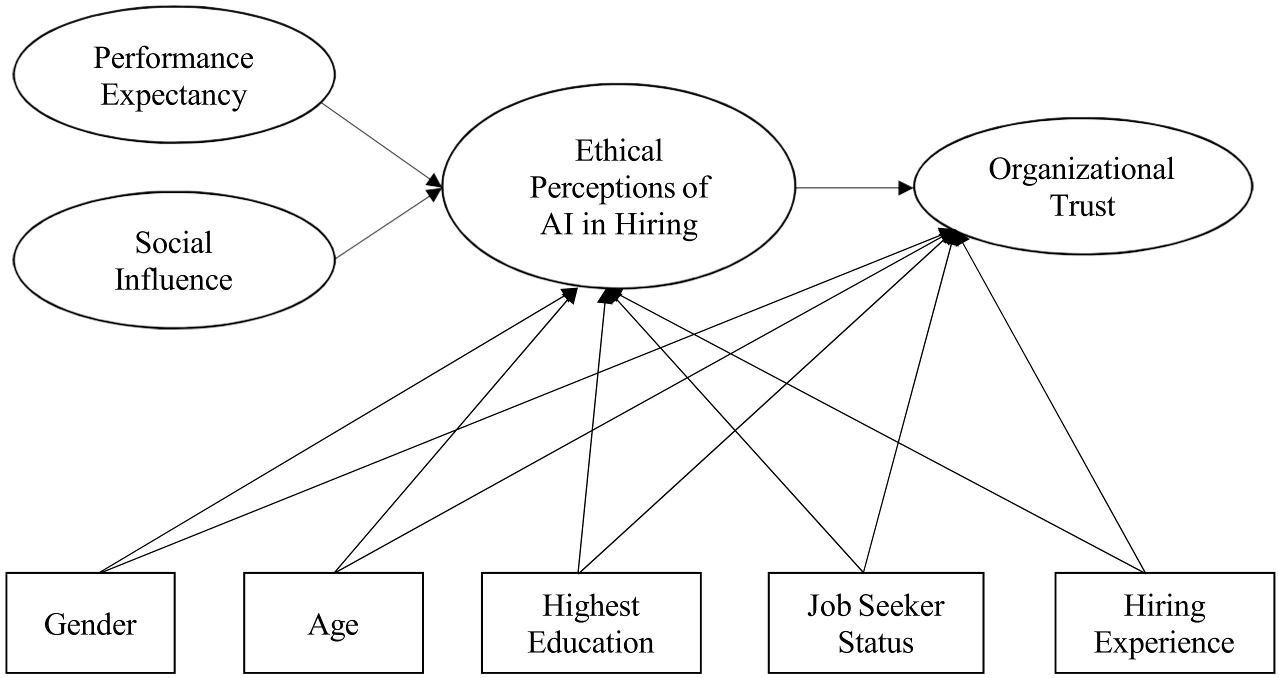


Fig. 1 Hypothesized structural model. Fig. 2 in “Appendix” provides SEM Results for the overarching research model

Finally, while we carefully designed our model based on theory and prior research, we cannot fully rule out reverse causality. To mitigate such concerns, we tested a model in which performance expectancy and social influence were related to ethical perceptions of AI in hiring, via organizational trust. We found that this model does not provide a better fit to the data (χ^2 (267, N = 305) = 451.82, CFI = 0.95, TLI = 0.94, RMSEA = 0.048, SRMR = 0.073) than our hypothesized model, further supporting our original model and hypotheses.

Supplementary Analyses

We ran additional analyses to examine whether ethical perceptions about the use of AI in hiring exhibited similar results across the three types of hiring methods that we identified through the EFA and confirmed with the CFA. Overall, we found that the patterns of relationships between performance expectancy and social influence and all three hiring methods factors were similar to those of our hypothesized structured model. Specifically, performance expectancy was positively related to archival (β = 0.50, p = 0.00), hurdle- process (β = 0.25, p = 0.00), and intrusive hiring methods (β = 0.31, p = 0.00). Also consistent with our earlier findings, social influence was not related to archival (β = − 0.05, p = 0.57), hurdle-process (β = 0.15, p = 0.09), or intrusive hiring methods (β = 0.13, p = 0.14). Interestingly, however, only archival and hurdle-process hiring methods were positively related to organizational trust (respectively, β = 0.31 and β = 0.40, both p = 0.00), while the intrusive hiring methods were not related to organizational trust (β = 0.09, p = 0.24). This latest result suggests that ethical perceptions about using AI in hiring are not consistent across the different types of hiring methods for which it is used, at least not in terms of its relationship with organizational trust.

Discussion

Theoretical Contributions and Practical Implications

Near the onset of the twenty-first century, Cordeiro (1997) suggested that in the increasingly complex ethical context that managers face, it is critical to stay alert and integrate technology-related ethics within the existing ethical frame- works used by organizations. A few years later, Martin and Freeman (2004) proposed that the confluence of technology and ethics carries with it an inherently value-laden situational relationship, whose impact within and beyond organizations is of particular importance to business ethics scholars (Martin & Waldman, 2022). Although discussion about the ethics of AI has gained traction in popular press and some critical areas such as medicine (Choi et al., 2016) and psychology (Turkle, 2011), the study of the ethics of AI in HRM is only recently garnering scholarly attention.

Given the exponential growth of AI in many aspects of business (Munoko et al., 2020) and its inevitable presence in HRM (Meyer, 2018; Prpic, 2020), this study is timely, and its implications highlight the need for proactive collabo- ration within the HRM and business ethics communities. Emerging evidence by business ethics scholars suggests that despite the advantages (e.g., accuracy, objectivity) that AI promises for HR practices, individual ethical perceptions about whether to trust the organizations that use AI-enabled tools may vary based on personal values (Keh & Xie, 2009) and past experiences (Fatma & Rahman, 2017), which will in turn impact other perceptions about the firm.

In particular, our study suggests that two antecedents from the unified theory of acceptance and use of technology (UTAUT), performance expectancy and social influence (Venkatesh et al., 2003), can be leveraged to connect individual ethical perceptions of AI to organizational trust. Specifically, regarding performance expectancy, the firm may have to choose between the time-saving benefits of using effective and accurate AI-enabled tools (IBM, 2018a; Peck, 2013) or the benefits that flow from having the trust of job seekers or even customers, such as more job applications (Morgan & Hunt, 1994; Parmigiani & Mitchell, 2005) and customer loyalty (Fatma & Rahman, 2017; Singh, et al., 2012).

Social influence is another factor that is expected to influence what individuals deem to be ethical. Whether the influence is coercive, such as from authority figures like doctors (Bozan et al., 2016), or more normative, such as from observing friends and family accepting and using a technology (Kijsanayotin et al., 2009), the moral reflective process that follows leads to perceptions that a thing is both acceptable and ethical (Rawls, 2001). Nonetheless, in our study social influence does not exert influence on perceived ethics of AI or lead to greater trust in the organizations that use it. This finding is noteworthy as it aligns with seminal work in social psychology about the forces affecting individual behavior, which suggests that peer-pressure is more likely to be effective in a group decision condition (Lewin, 1943). Another explanation for this result is that technology *acceptance* is not equivalent to perceiving it to be *ethical* (Hume, 2000). Acceptance and usage can be a practical matter, sometimes related to, but often separate from personal attitudes and values (Keh & Xie, 2009).

Another important facet of study is the acknowledgment that AI is a blanket term that refers to many distinct technologies (Zhang & Lu, 2021). This fact has implications for the relationship between general acceptance of a technology and the personal acceptance of it (Jan et al., 2012; Liang et al., 2007; Teo et al., 2003). As AI becomes ubiquitous, will trust in it, and the firms that use it, also become the norm? We do not expect this to be so. While some types of AI are becoming common, and trust in those types might become normal, AI refers to an ever-expanding set of contexts and applications. Effectiveness can impact trust (Greenwood & Van Buren III, 2010), and success in one use case, such as predicting movie preferences, is unlikely to impact trust in AI creating art, for instance, if AI is not effective at that task. Further, because trust in AI depends on task characteristics (Ramchurn et al., 2016), not all AI applications will be trusted equally. Just as an individual might trust genetic engineering technology in a food crop use case but not trust it in a human cloning use case, there will be differences in trust across the technology category of AI, depending on how it is deployed and to what end. Thus, in our study we included a variety of AI use cases across the entire range of the hiring process, which provide a glimpse into this issue.

Furthermore, during our initial analyses, we discovered that the list of hiring methods loaded into three broad types, which we coined ‘archival hiring methods’, ‘hurdle-process hiring methods’, and ‘intrusive hiring methods.’ As we followed up on this, we found that ethical perceptions about using AI in hiring are not consistent across all methods within the hiring process. Additional analyses revealed that organizations that use AI to perform intrusive hiring methods (e.g., analyzing job seeker’s social media information), even when they are perceived as being ethical, do not garner greater trust. This is consistent with work on trust in AI that has found a key difference in our perceptions of AI performing technical tasks versus tasks that require social intelligence (Gaudiello et al., 2016). We expect AI to be proficient at data analysis and tend to trust AI to do such tasks (Ramchurn et al., 2016). In contrast, trust is less likely to exist when AI perform tasks we perceive to require value judgments and social acumen (Gaudiello et al., 2016), especially when we have high self-confidence that humans could perform those tasks (Logg et al., 2019).

Our paper also has practical implications for HR managers. Specifically, we found that even when individuals perceive the use of AI to be ethical for more intrusive methods (e.g., to analyze audio or video of applicants), they do not perceive the organization as being trustworthy. As such, HR managers ought to be careful about the trade-offs of using AI blindly throughout the hiring process vs. deciding when and how to use AI in hiring. For example, they could use AI to screen applicants and assess applicants' characteristics (i.e., screening phase; Hunkenschroer & Luetge, 2022), but perhaps not venture into using AI to analyze social media information or analyze audio/video of applicants (i.e., assessment phase; Hunkenschroer & Luetge, 2022). This further suggests that, while AI can be beneficial by providing a more efficient process (Chamorro-Premuzic et al., 2019; Peck, 2013) and by optimizing and objectivizing hiring (Polli, 2019), HR managers need to be careful not to use AI across the board, especially as AI can be viewed as being detrimental to individuals' privacy (Dattner et al., 2019) and as being less fair than traditional methods (van den Broek et al., 2019).

Furthermore, this paper has implications for job seekers, especially those who place a strong emphasis on the trust relationship they have with their prospective employer (Klotz et al., 2013). If job seekers have expectations as to whether AI is used in hiring for performance-related motives (e.g., being more efficient), they are more likely to view the use of AI in hiring as ethical, and in turn to perceive the hiring organization as being trustworthy. Organizations can thus signal to job seekers that they are using AI to optimize and objectivize the hiring process (Polli, 2019). Finally, job seekers also need to make sure that they understand for what hiring methods AI is being used. Especially, if AI is used for more intrusive methods (e.g., analyzing their social media activity), job seekers are likely to put less trust on such hiring organizations, as they are likely to feel that their privacy is being violated (Dattner et al., 2019) and that AI might not accomplish the optimization and efficiency role it is intended to serve (Chamorro-Premuzic et al., 2019).

Limitations and Directions for Future Research

While we built upon prior research as we developed a list of hiring methods for this study by consulting both practical (e.g., Bauer et al., 2012; Pulakos, 2005) and scientific sources (e.g., McCarthy et al., 2017; Ryan & Ployhart, 2000), we also examined the factor structure of our data with an EFA and CFA. Although our list is representative of the various modern methods, we acknowledge that it is not comprehensive. Future research might fruitfully consider additional HR innovations to update the present list. In particular, future research might consider whether respondents are technology-savvy (i.e., a corresponding degree, hobby, or affiliation) and the extent to which this personal characteristic could influence their ethical perceptions towards certain AI hiring methods.

Furthermore, because we were interested in studying ethical perceptions of hiring methods, we recruited a balanced sample of participants, where 50% of them were actively job seeking and 50% were employed and had recent hiring experience. A fruitful avenue for future research should con- sider expanding our sample to study differences in ethical perceptions between job seekers and recruiters. Understanding recruiters' ethical perceptions of the use of AI in hiring and whether they impact their trust in the organization that they are recruiting for could offer useful insights about the ethical dynamics of AI at play in HRM.

We also note that attitudes and intentions can differ from actual behaviors (Weber & Gillespie, 1998). While intentions and actions are typically moderately correlated, there are specific cases where they are very strongly correlated (e.g., Hrubes et al., 2001) and cases where they are weakly correlated (Sheeran & Webb, 2016). Our survey instrument asked about perceptions rather than actual behaviors, thus future work might close this gap by utilizing data that demonstrates trust through behaviors and not just attitudes.

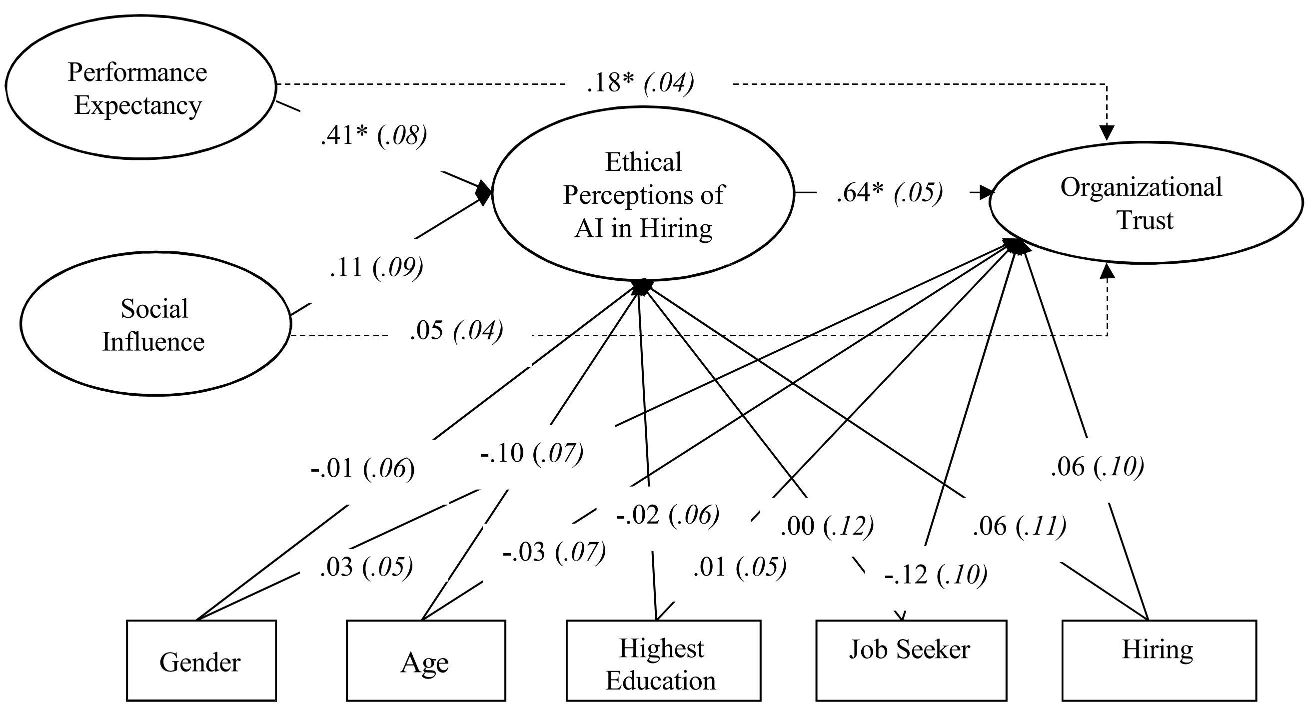
Finally, we used Prolific Academic (www.prolific.co) to recruit participants. Prolific is a highly trusted, recently developed source for subject recruitment which "explicitly caters to researchers" (Palan & Schitter, 2018, p. 22). Scholars in various disciplines have used this platform to recruit participants for research projects ranging from economics (e.g., Marreiros et al., 2017) to psychology (e.g., Callan et al., 2017) with superior response rates, reliability, and more diverse subject pools (for a full review see Palan & Schitter, 2018). Although highly commended, exploring our research questions in a new setting or platform and comparing results could further advance our knowledge of and trust in these new research tools.

Conclusion

Our study contributes evidence that performance expectancy affects individuals' ethical perceptions about the use of AI in the hiring process. Ethical perceptions, in turn, positively impact whether individuals trust the organizations that use AI. Our findings offer noteworthy theoretical and practical implications for ethics in HRM and inform policy implementation about the use of AI in hiring methods, especially as it pertains to acting ethically and trustworthily. Our research further highlights the importance of understanding whether and how individuals' acceptance of emerging technology and social vectors of influence in their environment, whether coercive or normative, influence their ethical perceptions that organizations using AI in hiring are trustworthy. Together, these findings offer unique insights about how ethical perceptions are formed in hiring, in the presence of emerging AI, and how technological effectiveness via ethical perceptions plays a critical role in organizational trust.

Appendix

See Fig. 2.



Note. * $p < .01$. Standard error in italic between parentheses. ——▶ direct effects

- - - - -▶ indirect effects

Fig. 2 SEM results for overarching research model

Survey Instrument

Definition of AI and Script

Artificial Intelligence **(AI)** refers to the ability of machines to perform tasks that typically require human intelligence, such as learning and problem solving. Machines can be programmed and trained to accomplish specific tasks by processing large amounts of data and recognizing patterns in the data. Some examples include speech recognition, self-driving cars, predicting movie preferences, and smart assistants.

Right now, imagine you are actively pursuing a job at an organization you would really like to work for. The recruiting process is often a multi-stage process, which includes screening, interviewing, assessment, and selection.

Hiring Methods

Instructions: Indicate the degree to which you consider the use of Artificial Intelligence (AI) to be an ethical practice during each of the following stages of the recruiting process. (1 = *very unethical;* 5 = *very ethical)*

1. AI being used for screening applicants to determine whether they meet the minimum job qualifications.
2. AI being used for assessing applicants' characteristics and traits such as intelligence, honesty, and personality.
3. AI being used to conduct applicant interviews.
4. AI being used to select which applicants will be hired.
5. AI being used to analyze social media information for traits and characteristics.
6. AI being used to analyze interview text (transcribed) for answer quality.
7. AI being used to analyze video of applicants for nonverbal behaviors.
8. AI being used to analyze still images of applicants for facial features.

9. AI being used to analyze audio of applicants for voice cues.
10. AI being used to analyze submitted documents from applicants.

Organizational Trust (Biswas and Suar, 2016)

Instructions: Imagine a company that actively utilizes Artificial Intelligence (AI) in various ways along the steps of their recruitment process. Indicate the extent to which you agree with the following items about the company. (1 = *strongly disagree;* 5 = *strongly agree)*

1. Employees' perception of employer having high integrity.
2. Employees' perception of employer treating them in a consistent, fair, and predictable fashion.
3. Employees' perception of employer being honest and truthful.
4. Employees' perception of employer's motives and intentions being good.
5. Employer being open and upfront with employees.

Performance Expectancy (Venkatesh et al., 2012)

Instructions: Indicate the extent to which you agree with the following items. (l = *strongly disagree;* 5 = *strongly agree)*

1. I find AI useful in my daily life.
2. Using AI helps me accomplish things more quickly.
3. Using AI increases my productivity.

Social Influence (Venkatesh et al., 2012)

Instructions: Indicate the extent to which you agree with the following items. (1 = *strongly disagree;* 5 = *strongly agree)*

1. People who are important to me think that I should use AL
2. People who influence my behavior think that I should use AL
3. People whose opinions that I value prefer that I use AL

Control Variables

Where do you currently reside?

1. USA
2. UK
3. Ireland
4. Other

What is your sex?

0. Female
1. Male
2. Prefer not to respond What is your year of birth?

What is your highest level of education?

1. Less than high school
2. High school
3. Some college/university
4. College/university degree
5. Post-graduate degree

Are you actively looking for a job?

0. Yes
1. No

How much experience do you have hiring new employees?

1. Not at all
2. A little
3. A moderate amount
4. A lot
5. A great deal

Data Availability The data that support the findings of this study are available from the corresponding author upon reasonable request.

Declarations

Conflict of interest The authors declare that they have no conflict of interest.

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