Seeming Ethical Makes You Attractive: Unraveling How Ethical Perceptions of AI in Hiring Impacts Organizational Innovativeness and Attractiveness

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Abstract

More organizations use AI in the hiring process than ever before, yet the perceived ethicality of such processes seems to be mixed. With such variation in our views of AI in hiring, we need to understand how these perceptions impact the organizations that use it. In two studies, we investigate how ethical perceptions of using AI in hiring are related to perceptions of organizational attractiveness and innovativeness. Our findings indicate that ethical perceptions of using AI in hiring are positively related to perceptions of organizational attractiveness, both directly and indirectly via perceptions of organizational innovativeness, with variations depending on the type of hiring method used. For instance, we find that individuals who consider it ethical for organizations to use AI in ways often considered to be intrusive to privacy, such as analyzing social media content for traits and characteristics, view such organizations as both more innovative and attractive. Our findings trigger a timely discussion about the critical role of ethical perceptions of AI in hiring on organizational attractiveness and innovativeness.

Keywords: AI ethics; Organizational attractiveness; Organizational innovativeness; Hiring methods

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Introduction

The ethics of Artificial Intelligence (AI) are increasingly highlighted in critical human contexts ranging from human resource management (Pan et al., 2022; Tambe et al., 2019; Vrontis et al., 2022) to medical diagnosis (Hamet & Tremblay, 2017). While the popular press has underscored the potential legal and ethical repercussions of using AI in the context of hiring (Dattner et al., 2019), there has been limited scholarly attention towards how ethical perceptions of AI impact those involved in the hiring process. On one hand, AI offers the potential to reduce human bias and optimize the hiring process (Houser, 2019; Lavanchy et al., 2023). On the other hand, there is evidence that AI-enabled tools can lead to algorithmic discrimination (Lambrecht & Tucker, 2019) and displacement (Brynjolfsson & McAfee, 2014) due to the potential for adverse impact to applicants with unconventional backgrounds (e.g., gaps on their resume) such as caregivers, individuals with disabilities, and those with a criminal background (Fuller et al., 2021). Notwithstanding, there is a lack of scholarly research that places an ethics lens on the influence of AI on applicants and on the organizations that use AI in hiring. This lack of research is likely the result of an important limitation in how AI is treated in the ethics literature.

Most prior work has focused either on the question of whether AI-driven practices are fair (e.g., Kasy & Abebe, 2021) or on the question of how trust in AI develops (Glikson & Woolley, 2020). In contrast, far less work has focused on how the ethical perceptions of AI influence the organizations that use it and their stakeholders. Although there is some evidence that specific AI practices are seen as ethical or unethical (Pistono & Yampokskiy, 2016), we know very little about how those perceptions shape an applicant's attraction to an organization that uses AI in hiring. For example, whereas the link between AI and attraction has received some attention in the marketing literature (for a review see Varsha et al., 2021), our understanding of how using AI in hiring practices is related to perceptions of the organization is close to nil (see Martin & Waldman 2022 for a discussion). One key exception is that ethical perceptions impact organizational trust (Figueroa-Armijos et al., 2022). Yet, we know little about other important perceptions of organizations, such as their attractiveness or innovativeness, that play key roles in critical organizational outcomes such as cost savings in hiring (Ritson, 2002), reduced turnover intentions (Alniacik et al., 2011), and even firm performance (Kashive & Khanna, 2017). Our study adds to this emerging field of study and offers fundamental theoretical and practical implications with regards to how ethical perceptions inform organizations' use of AI in human resource management (HRM) practices as a strategy to enhance their attractiveness. At the same time, our study contributes to adding an ethics lens to the evaluation of organizations' use of AI-enabled tools, an important first step to develop ethical and reliable AI systems (Telkamp & Anderson, 2022).

In this paper, we propose that ethical perceptions of AI in hiring is a key modern-day concern for organizations seeking to be innovative in their hiring practices and more attractive to applicants. There is a strong tendency in research on the ethics of AI to focus on the robots and algorithms more so than on the individuals and organizations that use AI-enabled tools. Here, rather than directing our attention to the AI algorithms, we consider whether and how individual ethical perceptions of the organizations that use AI in their hiring practices can enhance organizational attractiveness. We build on the person-organization (P-O) fit literature (Kristof, 1996) and social identity theory (Tajfel & Turner, 1979), which suggest that potential applicants seek out organizations whose (ethical) values fit well with their own, and that applicants consider the desirability of having such organizations become a part of their identity. Specifically, we expect that individuals who perceive the use of AI in hiring as ethical will also align and identify with organizations that use it in the hiring process.

The overarching goal of this paper is, thus, to explore how perceptions of the ethics of AI in hiring are related to the extent to which individuals are attracted to the organizations that use it, and how this relationship operates through perceptions of organizational innovativeness. To achieve this goal, we conducted two studies. The first examines whether and how ethical perceptions about the use of AI in hiring relate to organizational innovativeness and attractiveness. The second study replicates the first one with separation of measurement, namely by collecting first the independent variable (i.e., ethical perceptions about the use of AI in hiring), and then one week later the mediating and outcome variables (i.e., organizational innovativeness and organizational attractiveness). We collected our data from individuals who were either active job seekers or had recent hiring experience to capture perceptions across a range of perspectives and hiring methods (Figueroa-Armijos et al., 2022; McCarthy et al., 2017; Ryan & Ployhart, 2000). Across both studies, we find that ethical perceptions of using AI in hiring influence organizational attractiveness, both directly and indirectly, via organizational innovativeness.

This paper contributes to the growing research on AI ethics in HRM practices as a human context (Pan et al., 2022; Tambe et al., 2019; Vrontis et al., 2022). Whereas ethics and organizational attractiveness and innovativeness have been studied together (e.g., Belinda et al., 2018; Riivari & Lämsä, 2019), we seek to further understand whether and how ethical perceptions of using AI in hiring are likely to influence whether both job seekers and individuals with hiring experience view an organization as attractive and innovative. By doing so, we extend the integration of ethics in the P-O fit literature (Kristof, 1996) and social identity theory (Tajfel & Turner, 1979) by investigating ethical perceptions of AI in hiring as a mechanism that determines organizational attractiveness and innovativeness.

Furthermore, this paper highlights the critical role of incorporating an ethics lens in the organizational attractiveness literature (e.g., Chapman et al., 2005; Highhouse et al., 2003) by advancing our understanding of whether and how the use of AI in hiring influences applicants' attraction towards these organizations that use AI in hiring. More specifically, we extend research around organizational attractiveness (Highhouse et al., 2003) and organizational innovativeness (Slaughter et al., 2004) to the study of ethical perceptions of using AI in hiring. Finally, this study has theoretical and practical implications that inform HRM practices regarding AI ethics in the hiring process, especially as it pertains to attracting potential applicants and signaling innovativeness.

Theoretical background

AI Ethics in Hiring

Although relatively recent, hiring methods increasingly involve AI-enabled tools (Black & van Esch, 2020). AI is generally defined as the ability of machines or computer systems "to perform tasks normally requiring human intelligence" (OED, 2021). Approximately one third of organizations reported using AI-enabled tools in hiring in 2017 (Stephan et al., 2017), with this proportion reaching 40 percent by 2019 (Oracle, 2019) and 66 percent by 2022 (Stefanowicz, 2022). Some AI applications in hiring include tools which aim to identify a diverse pool of candidates (e.g., TalentSonar), score asynchronous video interviews (e.g., HireVue, Montage), evaluate cognitive abilities through the use of games (e.g., Pymetrics, Knack), and assess person–organization fit through the scraping of social media profiles (e.g., Entelo) (Gonzalez et al., 2019a). From the perspective of applicants, they are able to apply for jobs through organizations' websites or by using third-party sites (e.g., GlassDoor, Indeed, CareerBuilder, Monster). Such websites might be AI-enabled to filter the pool of applicants to assess P-O fit and identify ideal candidates (Bogle & Sankaranarayanan, 2012).

Although the implementation of AI-enabled systems started before the 21st century (Franklin & Graesser, 1996), along with its discussion in the business ethics literature (see Khalil, 1993), its broad use in hiring is relatively recent (Black & van Esch, 2020) with limited research examining its effects, risks (Levashina et al., 2014), and ethical implications (Figueroa-Armijos et al., 2022). Indeed, advancements in AI technologies are reshaping hiring methods at an accelerated pace (Derous & de Fruyt, 2016; Ryan et al., 2015) and are expected to continue to disrupt hiring processes for years to come (van Esch et al., 2019). On the one hand, many organizations and job applicants alike consider some features of AI to be ethically superior (Tambe et al., 2019). For example, HR specialists across industries and locations endorse AI-enabled tools and platforms citing their objectivity (Konradt et al., 2013), impartial accuracy (McDonald et al., 2017), and speedy delivery of hiring outcomes (Arthur et al., 2009; Dineen et al., 2004; McCarthy et al., 2017) as ethical benefits.

On the other hand, the increased use of AI-enabled tools is also leading to a rise in AI ethical failures (Kaplan & Haenlein, 2019; Whittaker et al., 2018). For example, algorithms are often found discriminatory towards legally protected demographic categories including women and minorities (Bertrand & Mullainathan, 2004; Whittaker et al., 2018), and individuals with disabilities (Lambrecht & Tucker, 2019) who may have a gap on their resume or a dissimilar track record from the norm that the embedded metrics in the algorithm may identify as inferior (see Islam & Greenwoord, 2022 for a discussion on the ethics of metrics). Various large companies including Amazon, Microsoft, Apple, and IBM have been faulted and scrutinized for AI-enabled discriminatory technologies that produce 'unintentional' biased metrics or differing outcomes for these groups (BBC, 2019; Buolamwini & Gebru, 2018). Although some of these cases of AI ethical failures have been inspected and corrected, some may still be going unnoticed or unreported (Kelley, 2022).

Further, some of the critical risks of AI use in hiring involve data privacy or privacy loss for applicants and legal implications for organizations (Gonzalez et al., 2019a). In the European Union, for instance, the General Data Protection Regulation (GDPR), passed in 2016, requires firms to disclose their use of AI to applicants and clearly explain how their data will be used in the decision process (Liem et al., 2018). In the United States, state-level legislation is emerging to require firms to obtain applicants' consent prior to their interaction with AI-enabled tools and platforms used in hiring (Bologna, 2019). In addition, legislation such as HIPAA, introduced in the US in 1996, obliges AI operators to stipulate the specific data needed for a particular objective in order to protect sensitive health data potentially available to AI-enabled tools via social media networks (Weintraub, 2017). Yet, despite the presence of preventive legislative statutes, research on the appropriateness, fairness, and validity of AI in hiring methods still lags behind the accelerated pace of adoption of AI-enabled tools in HR practices (Derous & de Fruyt, 2016; Goodman, 2017).

Beyond legislation, the hiring process involves various complex criteria which are governed not only by legal statutes, but also by professional and ethical structures (Gonzalez et al., 2019a). These frameworks might be violated when an algorithm acquires and utilizes data that is irrelevant for a specific HR goal or is legally inappropriate in context (e.g., age, gender identity, race, ethnicity, pregnancy, civil status, religious affiliation, mental or physical disability, criminal record) (Hunkenschroer & Kriebitz, 2022; Tonidandel et al., 2018). Furthermore, AI-enabled tools can capture behavioral and physiological characteristics, such as biometrics, as part of the hiring process (van Esch et al. 2019) which when left alone to the decision-making of the AI system might be considered unfair criteria[1]. In addition to irrelevance and illegality of data mentioned above, unfairness is likely to be perceived when algorithms perpetuate historical bias because they are trained on data that was generated in an environment of discriminatory practices (Lambrecht & Tucker, 2019). Additional fairness concerns can originate from a lack of familiarity with how AI works in hiring (Johnson & Verdicchio, 2017), the lack of interpersonal communication and personalized treatment (Gonzalez et al., 2019b), and the perceived lack of control over the process (Leventhal, 1980).

Moving forward, the ethics of AI in hiring revolve around not only whether the AI-enabled tools introduced are valid (i.e., reliable and accurate), but whether they are known,

[1] For a review see John-Matthews et al. (2022)

accepted, and endorsed by applicants (Weinert et al., 2020), organizations (Alder & Gilbert, 2006), and society at large (Glikson & Woolley, 2020) to avoid a responsibility gap where no human or moral duty is held responsible for the actions of AI-enabled tools (Johnson, 2015). Applicants highly value HR practices that are procedurally fair, making such practices vital to attract the best candidates (Bangerter et al., 2012). Indeed, a candidate's attraction and attitude towards an organization is paramount; considered as more important than many other elements of the hiring process such as job description and job security (Holm, 2014).

Ethical Perceptions of AI in Hiring and Organizational Attractiveness

Organizational attractiveness is a distinct factor for applicants and organizations, especially as firms seek to attract the best candidates (Ewing et al., 2002). Organizational attractiveness is positively linked to positive attitudes in interested applicants (Berthon et al., 2005), cost savings in hiring (Ritson, 2002), reduced turnover intentions (Alniacik et al., 2011), and firm performance (Kashive & Khanna, 2017). The current wave of work in this area seeks to understand how individual differences (e.g., ethical perceptions in our study) are related to organizational attractiveness. There are at least two explanations for why ethical perceptions of using AI in hiring makes organizations attractive to some.

First, the P-O fit literature suggests that likes attract each other (Schneider, 1987). P-O fit refers specifically to the compatibility of an employee and their work environment (Kristof, 1996; Kristof-Brown et al., 2005). In support of this perspective, research shows that both objective attributes (e.g., Chapman et al., 2005) and perceived attributes (Slaughter & Greguras, 2009) of an organization lead to greater applicant attraction when they consider themselves to be similar to those attributes.

Second, attraction to an organization can also occur when job seekers view the prospective employer as an identity symbol that portrays their preferred personal social identity (Highhouse et al., 2007). This perspective builds on social identity theory (Tajfel &

Turner, 1979) to suggest that individuals are attracted to an organization because, through personal affiliation, that organization's symbolic features can in turn, communicate to others that those symbols also represent their personal identity. In hiring, applicant perceptions are key (Nikolaou et al., 2019). Thus, if a job seeker believes it is ethical to use AI in hiring, or that doing so is innovative, they will be attracted to companies that use AI in hiring so they can leverage those organizational attributes as a means to expressing their personal identity.

In a study by Ehrhart and Ziegert (2005), candidates recognize signals during the hiring process not only as objective, but also as subjective indicators of their attraction towards the organization. Perceptions of organizational attractiveness are also positively enhanced by the use of technology in hiring when applicants perceive it to be objective (Minge & Thüring, 2018), user-friendly (Howardson & Behrend, 2014), efficient (Gonzalez et al., 2019a), innovative (Sommer et al., 2017), and aligned with their personal values (Vanderstukken et al., 2016). In this paper, we respond to numerous calls to examine the impact of ethical implications of AI use (e.g., Munoko et al., 2020) in the context of hiring (Hunkenschroer & Luetge, 2022), an underexplored research area which involves unique ethical challenges (e.g., Tambe et al., 2019) directly affecting people's careers (Hunkenschroer & Luetge, 2022) and organizations (Haenlein et al., 2022).

A recent US-wide experiment showed that individuals are generally concerned about the risks of AI applications and have mixed ethical attitudes towards them (Araujo et al., 2020). Ethical risks from the use of AI can emerge from human value commitments which are deliberately or unconsciously built into the system's design and features (Johnson, 2015; Shilton et al., 2013). In other words, behind every AI-enabled tool there is a human designer whose moral or personal values[2], which influence their ideology and moral judgments (e.g.,

[2] Shilton et al. (2013) provides a framework for "Values in Design" (VID) which can be found in emerging technologies, including "privacy, trust, security, safety, community, freedom from bias, autonomy, freedom of expression, identity, dignity, calmness, compassion, and respect" (p. 5).

stereotyping) (Esmaeilzadeh, 2020), may reflexively become integrated as "concrete features" (Johnson, 2000) in the technological artifacts they create (Friedman & Nissenbaum, 1997), potentially leading to discrimination. Consequently, ethical risks can also occur in the form of unanticipated outcomes observed during application in human environments (Martin et al., 2019), such as AI-enabled tools in hiring disqualifying candidates for having unconventional backgrounds (e.g., individuals who are caregivers, disabled or have a criminal background) (Fuller et al., 2021) or for belonging to certain legally protected demographic categories that had been previously lacking in that industry (Lambrecht & Tucker, 2019).

Although multidisciplinary conversations are emerging to devise new ethical frameworks around AI design (see Haenlein et al., 2022 and Martin et al., 2019), far less attention is directed at the role of individuals and organizations on the development and deployment of AI systems inside and outside the firm (Martin et al., 2019). Thus, while we see mixed reactions to the ethicality of AI hiring practices, organizations are, nevertheless, moving forward in their adoption of these practices, perhaps because they know that job candidates who are attracted to organizations that use AI-enabled tools are more likely to complete and submit their job applications (Holm, 2014). Thus, as described above, and consistent with both the P-O fit model and social identity theory, we propose that applicants who perceive the use of AI as being ethical are more likely to perceive a fit and identify with organizations that use AI in their hiring process, and hypothesize the following:

Hypothesis 1. Ethical perceptions about the use of AI in hiring will be positively related to organizational attractiveness.

While we carefully derived our hypothesis from theory, in this case from the P-O fit model and social identity theory, we acknowledge that organizational attractiveness may also influence ethical perceptions of using AI in hiring. Indeed, people who are attracted to work for a company, they may perceive it to be ethical in its practices, simply to avoid the cognitive dissonance of wanting to work for an unethical organization.

Ethical Perceptions of AI in Hiring and Organizational Innovativeness

Humans tend to ascribe human traits, such as personality, to organizations (Plummer, 2000; Tom, 1971), which has led to the development of organizational personality measures such as innovativeness (Slaughter et al., 2004; Lievens et al., 2005). Subsequent work also shows whether and how these perceptions of organizational personality are related to organizational attractiveness (Lievens & Highhouse, 2003; Schreurs et al., 2009; Van Hoye et al., 2013). For example, Lievens and Highhouse (2003) found that organizational innovativeness and competence were positively related to organizational attractiveness. Interestingly, though, Van Hoye et al. (2013) did not find a significant relationship between organizational innovativeness and organizational attractiveness, but a positive one between competence and attractiveness. Finally, in another study, Schreurs et al. (2009) found that an organization's perceived prestige and competence were related to organizational attractiveness.

Organizational innovativeness is widely considered a key element to achieving competitive advantage (Azadegan & Dooley, 2010; Yeung et al., 2007). While the notion of organizational innovativeness seems to be important in various business functions, it is not always clear what exactly it is. Organizational innovativeness has been measured in at least 13 distinct ways in recent research on the topic (for a review see Sommer et al., 2017), including the degree of innovativeness across the portfolio of products, R&D intensity, the number of patents, organizational flexibility, willingness to change, and a variety of cultural factors.

Despite the lack of consensus on what organizational innovativeness is, the myriad operationalizations can be condensed, roughly, into product portfolio innovativeness and innovation culture (Sommer et al., 2017). In the context of HR practices, organizational innovativeness does not typically lead to new products and services, but it can yield ideas that lead to new processes within the firm and new cultural or personality elements.

Firm culture, generally, is a key consideration for job seekers as they determine which employers they prefer (Ehrhart & Ziegart, 2005; Cable & Graham, 2000). Innovation culture seems to be one of the preeminent elements within this process. Indeed, job seekers view companies that they perceive as innovative to be more exciting, original, and interesting (Slaughter & Greguras, 2009). Job seekers also favor companies with flexible and creative cultures that are willing to invest in new ideas (Kekäle & Kola-Nystrom, 2007). Importantly, the very nature of innovativeness suggests that if everyone has it, then no one has it.

In practice, there is a great deal of variation across firms in their perceptions of their own innovative preparedness with very few firms truly being highly innovative in their own eyes. For instance, a recent survey of CEOs at companies innovating with data analytics capabilities, only 4 percent believed their firm to be largely prepared to use the new tools, with a staggering 41 percent reporting not being prepared at all (IBM, 2018). These findings suggest that job seekers are also likely to perceive some firms as far more innovative than others, with the few at the top benefitting from this critical element of their brand reputation. From a brand management perspective, Mosley (2012) finds that, for potential employees, innovativeness is one of the most sought-after brand ideals. Further, Sommer and colleagues (2017) find that innovative product portfolios and innovation culture both lead to higher perceptions of organizational attractiveness.

In our theorizing of how AI perceptions impact organizational attractiveness, we focus on organizational innovativeness in terms of how a company is perceived. Indeed, AI is increasingly becoming a critical tool for innovation across industries (Weinert et al., 2020), from manufacturing (Srinivasan, 2014) to medicine (Tsang et al., 2017). In HRM, organizations use AI systems for recruitment and selection in pursuit of higher efficiency by sorting through large applicant pools in less time (Das et al., 2018; Upadhyay & Khandelwal, 2018). Accordingly, organizations which use AI in hiring might achieve higher efficiency, while also signaling innovativeness to applicants (van Esch et al., 2020), causing those that value innovativeness to perceive those organizations to be more attractive. Meanwhile, some candidates applying for jobs at firms that use AI can be attracted to the novelty of the technology (Venkatesh et al., 2016), consistent with the P-O fit literature (Kristof, 1996; Kristof-Brown et al., 2005). Indeed, the use of AI in recruiting is increasingly associated with technology-oriented companies or organizational innovativeness (Albert, 2019).

While we expect innovativeness to influence the attractiveness of organizations, we also expect ethical perceptions to influence how innovative an organization is perceived to be. Several prior studies suggest that being ethical is a precondition for perceived organizational innovativeness (Martins & Terblanche 2003; Sarros et al., 2008), with others going so far as to suggest that such a relationship is "common sense" (Büschgens et al., 2013). Still, this research is vague about the distinct ethical values (or mechanisms) that lead to perceptions of innovativeness. Two recent studies suggest an answer to this question when they explain the importance of congruence in ethics models (Pučėtaitė et al., 2016; Riivari et al., 2012). Similar to P-O fit, both studies theorize that congruence of personal and organizational values causes employees in ethical organizations to more vigorously pursue congruent attributes, or in other words, any moral or performance attributes that they consider themselves to share with the firm culture or personality. Thus, employees in firms that identify, for instance, as both ethical and innovative will strive for congruence through being more innovative when they perceive that they are ethical (or vice versa).

Further, this mechanism also operates at an external level where observers (such as job seekers) take the achievement of one ideal (e.g., ethicality) as a sign that the firm is also achieving its other ideals (innovativeness). Thus, akin to the halo effect (Nisbett & Wilson,

1977) or spillover effects, when a firm utilizes practices that are seen as ethical, if those practices are also perceived as innovative, the perception of ethics will also enhance the perception of innovativeness. In the case of a job seeker that perceives innovative AI hiring practices to be ethical, their ethical approval also boosts their perceptions of the other attributes connected to the practice, such as it being innovative. We thus hypothesize that:

Hypothesis 2. Ethical perceptions about the use of AI in hiring will be positively related to organizational attractiveness, via organizational innovativeness.

Study 1

Sample and Procedure

We used Prolific (http://www.prolific.co), an online research platform with a demographically diverse pool of more than 130,000 vetted respondents, to recruit participants. Scholars and organizations (e.g., European Commission, Google) are increasingly identifying Prolific as a reliable source of diverse, high-quality survey data (Palan & Schitter, 2018; Tilcsik, 2021). In fact, Prolific scores higher in comparative analyses of survey platforms on psychometric scales and honest responding, consistently delivering high levels of internal reliability, along with low levels of failure rate on sensitivity analyses, and a high level of replicability of prior findings (Peer et al., 2017). Because we were interested in studying individual ethical perceptions of hiring methods, we recruited 305 participants, 50% who were actively job seeking, and 50% who were currently employed and had recent hiring experience. The sample consisted of 78.6% participants from the UK, 11.8% from the US, 8.3% from Canada, and 1.3% from Ireland. On average, participants were 35.6 years old; 59% were female; 41.3% had a college degree, 22.9% a post-graduate degree, 25.6% some college education, and 10.2% had a high school degree.

Participants received a cover sheet with information about the study and, after agreeing to participate, they were directed to a web-based survey where they were presented with the following definition: "*Artificial Intelligence (AI)* is 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." After providing this definition for AI, we asked participants to read the following script: "*imagine you are actively pursuing a job at a company you would really like to work for. The recruiting process is often a multi-stage process, which includes screening, interviewing, assessment, and selection. Indicate the degree to which you consider the use of Artificial Intelligence to be an ethical practice during each of the following stages of the recruiting process.*"

Following the script, participants were presented with several items to express their ethical perceptions about hiring methods at various stages of the hiring process. Participants were then instructed to "imagine a company that actively utilizes Artificial Intelligence (AI) in various ways along the steps of the hiring process" before responding to items about their perceptions of the organization (i.e., organizational innovativeness, organizational attractiveness). At the end of the survey, survey participants were presented with questions about their demographic characteristics.

Measures

Hiring Methods. We adopted the measure developed by Figueroa-Armijos et al. (2022), which integrates prior research and practice from both managerial (e.g., Pulakos, 2005) and scholarly sources (e.g., McCarthy et al., 2017; Ryan & Ployhart, 2000). Accordingly, we included the 10 hiring methods developed by Figueroa-Armijos et al. (2022), which range 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," "analyzed 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" (p. 7). Participants were asked to respond on a five-point scale (1 = very unethical; 5 = very ethical) to "indicate the degree to which you consider the use of Artificial Intelligence to be an ethical practice during each of the following stages of the recruiting process."

To identify factors on which the different items loaded, we ran an Exploratory Factor Analysis (EFA). As shown in Table 1, a Principal Components Analysis (PCA) with varimax rotation indicated that the ten methods loaded onto the same three distinct factors (i.e., with eigenvalue greater than one) as those identified by Figueroa-Armijos et al. (2022), namely "archival" hiring methods (i.e., centered around submitted materials and documents), "hurdle-process" hiring methods (i.e., centered around the multiple hurdle model of hiring) (see Aiken & Hanges, 2017), and "intrusive" hiring methods (i.e., centered around methods more intrusive to privacy) (see table 1 for details for each). Table 1 further indicates the loadings for the items onto the three factors.

We selected the "intrusive" label for the last factor because it contains methods that are widely perceived as intrusive to privacy. For example, data that utilize or capture personal biological characteristics, such as skin tone in facial automated recognition (Buolamwini & Gedru, 2018), are concerning to most individuals (Bansal & Gefen, 2010). Similarly, many consider the use of social media data, such as pregnancy or religious affiliation (Hunkenschroer & Kriebitz, 2022), to be a privacy intrusion, especially when done without their knowledge or permission (Gruzd & Hernandez-Garcia, 2018; Jacobson, et al., 2020). All factor loadings were above the recommended cut-off (i.e., factor loadings ≥ .40; Hinkin, 1998). The three factors combined explained 73% of the variance. The reliability coefficient (Cronbach's alpha) for this scale is .86.

Insert Table 1 about here

Organizational Innovativeness. We measured organizational innovativeness with 7 items from Slaughter et al.'s (2004) organizational personality scale. Sample items include "interesting," exciting," and "creative." Participants responded on a five-point scale (1 = strongly disagree; 5 = strongly agree). The reliability coefficient for this scale was .86.

Organizational Attractiveness. We measured organizational attractiveness with a 5-item scale from Highhouse et al. (2003). Sample items include "This company is attractive to me as a place for employment" and "A job at this company is very appealing to me." Participants responded on a five-point scale (1 = strongly disagree; 5 = strongly agree). The reliability coefficient for this scale was .93.

Control Variables. Consistent with prior work in business ethics, we anticipated that ethical perceptions of AI in hiring amongst respondents may differ depending on their demographic characteristics. Age, gender, and educational attainment, in particular, are known to influence an individual's ethical perception of AI and data in general (Crockett et al., 2021). Further, age, gender, and experience impact the processing of new or complex information which affects an individual's ability and willingness to learn, adapt to, and accept technology (Morris et al., 2005), including interacting with AI (Hermann, 2022). Younger individuals, for example, are more likely to accept technology and assume it works well compared to older individuals (Venkatesh et al., 2012). At the same time, Dawson (1997) and Borowski and Ugras (1998) argue that cumulative age and experience affect both men and women's ethical attitudes, with older individuals exhibiting stronger ethical values. In fact, some ethics scholars argue that work experience may be the strongest influencer in ethical sensitivity

(Luthar & Karri, 2005). Thus, we controlled for gender, age, highest education, and hiring experience (Anderson, 2003). Participants reported their *age*, *gender* (0 – female; 1 – male), and their *highest education* (1 – less than high school; 2 – high school; 3 – some college; 4 – college degree; 5 – post-graduate degree). Finally, we asked participants to report, using a five-point scale (1 = strongly disagree; 5 = strongly agree) the extent to which they have *experience hiring* employees.

Results

Descriptive statistics and correlations in Table 2 reveal that ethical perceptions about the use of AI in hiring were positively related to organizational innovativeness (r = .29, $p < .001$) and organizational attractiveness (r = .52, $p < .001$). We also found a positive correlation between organizational innovativeness and organizational attractiveness (r = .45, $p < .001$).

Insert Table 2 about here

Measurement Model and Hypothesized Structural Model. We tested the model through structural equation modeling using maximum likelihood in STATA 17.0. We applied five indices 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). We relied on Hu and Bentler's (1999) cutoff criteria for the various fit indices. For the CFI and TLI, indices above .95 represent excellent fit, between .90 and .95 good fit, and below .90 poor fit. In the RMSEA, indices between .01 and .05 represent excellent fit, between .05 and .08 good fit, and above .08 poor fit. In the SRMR, indices below .08 are generally considered good fit. Consequently, the measurement model provided a good fit to the data (χ^2 (279, N = 603) = 1057.84, CFI = .90, TLI = .90, RMSEA = .068, SRMR = .067). Factor loadings are shown in Table 2. We also found that the hypothesized model provided a good fit to the data (χ^2 (283, N = 603) = 1070.37, CFI = .90, IFI = .90, RMSEA = .068, SRMR = .068).

Insert Table 3 about here

Hypotheses Testing. As shown in Table 4, Hypothesis 1 was supported, indicating that ethical perceptions about the use of AI in hiring is positively related to organizational attractiveness ($\beta = .47$, $p < .001$). Hypothesis 2 was also supported, with a significant indirect effect, indicating that ethical perceptions about the use of AI in hiring would be indirectly and positively related to organizational attractiveness, via organizational innovativeness ($\beta = .28$, $p < .001$). Furthermore, we found that ethical perceptions about the use of AI in hiring were positively related to perceptions of organizational innovativeness ($\beta = .38$, $p < .001$). Our results support the idea that organizations who used AI in hiring were perceived as being more innovative, and in turn more attractive[3]. For Study 1, 15% of the variance in innovativeness was explained by our model, whereas 48% of the variance in attractiveness was explained. Results remained unchanged without the control variables.

Insert Table 4 about here

Supplementary Analyses. We conducted supplementary analyses to explore whether ethical perceptions about the use of AI in hiring revealed similar results across the three types of hiring methods from the Exploratory Factor Analysis (EFA). Interestingly, we identified differences in the patterns of relationships between the three factors and organizational innovativeness and organizational attractiveness. Specifically, organizational attractiveness

[3] Since we collected data from both job seekers and employed individuals with hiring experience, we ran additional analyses to examine whether and how the hypothesized structural model varied depending on whether respondents were job seekers or not. We found that the results were equivalent for both types of participants.

was positively related to ethical perceptions of the hurdle-process methods ($\beta = .32$, $p < .001$), but not of the intrusive hiring methods ($\beta = .15$, $p = .056$) or of the archival methods ($\beta = .01$, $p = .951$). Noteworthily, though, only the ethical perceptions of the intrusive hiring methods were positively related to organizational innovativeness ($\beta = .18$, $p < .05$), and indirectly to organizational attractiveness ($\beta = .08$, $p < .05$). These results are novel as they suggest that the influence of ethical perceptions of using AI in hiring is not consistent across hiring methods. Indeed, for organizations that use AI in intrusive ways, such as analyzing social media information for traits and characteristics, individuals that consider those methods to be ethical viewed such firms as more innovative and attractive. In contrast, it did not seem to matter if individuals perceived the other types of AI uses to be ethical or not. Organizations that use AI for hurdle-process (e.g., assessing applicants' traits, selecting which applicants will be hired) or archival tasks (e.g., screening applicants to determine whether they meet the minimum job qualifications) were not seen as more or less innovative or attractive whether individuals considered those practices to be ethical or not.

Study 1 Discussion

Findings from Study 1 support the idea that having higher ethical perceptions about the use of AI in hiring is related to higher perceptions of both innovativeness and attractiveness towards organizations that use AI in hiring. It is important to note that our findings also suggest that those who have lower ethical perceptions about the use of AI in hiring will have lower perceptions of innovativeness and attractiveness towards organizations that use AI in hiring. Furthermore, our findings also provide some nuance that the influence of ethical perceptions on innovativeness and attractiveness is likely to vary depending on the type of AI hiring method (i.e., archival, hurdle-process, intrusive). While we carefully designed our study drawing from theoretical underpinnings, we cannot completely rule out the potential for reverse causality. In this case, perhaps, organizational attractiveness influenced one's ethical perceptions about using AI in hiring[4]. As such, while the results from Study 1 are interesting and novel, they also have some limitations. For example, the data was collected from self-reported measures at a single point in time, which carries higher risk of common method variance (Podsakoff et al., 2012). Furthermore, most participants were from the UK, which limits the generalizability of our findings. To address these concerns, we conducted a second study in which we addressed some of the limitations from Study 1. Specifically, in Study 2, we collected data from US job seekers and employed individuals with hiring experience at two points in time, separating the script and measure of ethical perceptions from the measures of organizational innovativeness and attractiveness.

Study 2

Sample and Procedure

For Study 2, we also recruited participants using the Prolific platform (www.prolific.co). We asked the participants to complete two surveys separated by one week. At time 1, we recruited 280 participants from the US, among which 50% were actively job seeking, and 50% were employed with hiring experience. At time 2, 226 of these initial participants responded to the second survey, for a retention rate of 81%. On average, these 226 participants were 36.3 years old; 64% were female; 44% had a college degree, 20% a post-graduate degree, 28% some college education, and 9% a high school degree.

We followed the same procedure as in Study 1. In the first survey, we provided the participants with the same definition of AI, the same script, and the same items about their ethical perceptions of various hiring methods, and the same demographic items, as in Study 1.

[4] While we cannot completely rule out reverse causality, we tested an alternative model, in which organizational attractiveness would influence ethical perceptions of using AI in hiring both directly and indirectly via organizational innovativeness. We found that organizational attractiveness was positively related to these ethical perceptions, but only directly. The indirect relationship via organizational innovativeness was not significant, neither was the relationship between innovativeness and ethical perceptions of using AI in hiring. These findings provide further support to our theory-driven model.

In the second survey, we presented them with the same definition of AI and its potential use across hiring methods, followed by the same instructions and items about their perceptions of organizational innovativeness and organizational attractiveness as in Study 1.

Measures

Hiring Methods. We used the same items as in Study 1. To provide further validation for our measure, we conducted a CFA using STATA 17.0. To ensure proper structure, the λ values for all items should be both large ($\lambda \geq .30$) and significant ($p < .05$) (Hair et al., 1998). In support of the three-factor structure identified in the Study 1 sample, results of the CFA indicated that λ values ranged from .65 to .83 for the three items of the archival factor, from .73 to .87 for the three items of the hurdle-process factor, and from .66 to .91 for the four items of the intrusive factor. Thus, all values exceeded the recommended cut-off ($p < .01$).

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 acceptable fit to the data (χ^2 (32, N = 281) = 131.82, CFI = .94, TLI = .91, RMSEA = .106, SRMR = 0.062). Importantly, we also found that the three-factor structure provided a significantly better fit than a one-factor structure with all items loading on the same factor ($\chi2$ change = 220.53 with 3 Δdf, $p < .01$). Results from the CFA analyses provide further validation for the three-factor hiring methods structure. The reliability coefficient for this scale was .77.

Organizational Innovativeness. We measured organizational innovativeness with the same items as in Study 1. The reliability coefficient for this scale was .85.

Organizational Attractiveness. We measured organizational attractiveness with the same items as in Study 1. The reliability coefficient for this scale was .92.

Control Variables. We collected the same control variables as in Study 1.

Results

Table 5 presents the descriptive statistics and correlations. Examination of these results indicates that ethical perceptions about the use of AI in hiring was positively related to both organizational innovativeness (r = .42, $p < .001$) and organizational attractiveness (r = .51, $p < .000$). We also found a positive correlation between organizational innovativeness and organizational attractiveness (r = .67, $p < .001$).

Insert Table 5 about here

Measurement Model and Hypothesized Structural Model. As in Study 1, the hypothesized model was tested through structural equation modeling using maximum likelihood in STATA 17.0. We found that the measurement model provided a very good fit to the data (χ^2 (279, N = 226) = 459.39, CFI = .94, TLI = .94, RMSEA = .054, SRMR = 0.053). Factor loadings are shown in Table 3. We also found that the hypothesized model provided a very good fit to the data (χ^2 (283, N = 226) = 464.82, CFI = .94, IFI = .94, RMSEA = .054, SRMR = .055).

Hypotheses Testing. As shown in Table 6, Hypothesis 1, which proposed that ethical perceptions of the use of AI in hiring are positively related to organizational attractiveness was supported ($\beta = .31$, $p < .001$). Hypothesis 2, which proposed that ethical perceptions of the use of AI in hiring are indirectly and positively related to organizational attractiveness, via organizational innovativeness was also supported, with a significant indirect effect ($\beta = .50$, $p < .001$). We also found that ethical perceptions about the use of AI in hiring were positively related to perceptions of organizational innovativeness (β = .51, $p < .001$)[5]. For Study 2, 31% of the variance in innovativeness was explained by the model, and 59% of the variance in attractiveness. As for Study 1, results remain unchanged without the control variables. Figure 1 provides a depiction of the SEM model and path coefficients for both studies.

Insert Table 6 about here

Insert Figure 1 about here

Supplementary Analyses. As for Study 1, we conducted supplementary analyses to examine whether ethical perceptions of the use of AI in hiring exhibited similar results across the three types of hiring methods, which we validated through the Confirmatory Factor Analysis (CFA) in Study 2. Consistent with our Study 1 findings, we found differences across the three hiring methods in the relationships between ethical perceptions and organizational innovativeness and organizational attractiveness. Specifically, we found that only ethical perceptions of intrusive hiring methods were positively related (directly) to organizational innovativeness (β = .39, $p < .01$) and (indirectly) to organizational attractiveness (β = .24, $p < .01$). However, in contrast with Study 1, ethical perceptions of intrusive hiring methods were positively and directly related to organizational attractiveness (β = .25, $p < .01$). We note that, also in contrast with Study 1, we did not find organizational attractiveness to be related to ethical perceptions of the hurdle-process hiring methods (β = -.02, $p = .866$). Overall, these findings confirm our main conclusion that whether individuals consider intrusive AI practices to be ethical or not has a substantial bearing on their perceptions of the innovativeness and attractiveness of the organizations that use them.

[5] As for Study 1, we ran additional analyses to examine whether the hypothesized structural model varied depending on whether respondents were job seekers or not. We found that the results were equivalent for both types of participants.

General Discussion

The ethics of using AI has been of keen interest across society and disciplines for decades (see Khalil, 1993 and Franklin & Graesser, 1996 for early discussions), but interest in the topic has sharply increased in recent years (Vrontis et al., 2022), especially in the HRM and hiring context. Rather than focusing on the algorithms, we consider the importance of individual ethical perceptions of the organizations that use AI in their hiring practices, and whether and how these can enhance organizational attractiveness. In this paper, we found that the higher the ethical perceptions of using AI in hiring practices, the more innovative both applicants and individuals with hiring experience found the organization, and the more attracted they were to this organization. Interestingly, these results also suggest that individuals with lower ethical perceptions about AI in hiring will find organizations who use AI in hiring to be less innovative and attractive. Additional analyses also suggested that these findings are not equal across the three types of hiring methods (i.e., archival, hurdle-process, intrusive; Figueroa-Armijos et al., 2022). Indeed, our results suggest that higher ethical perceptions of using AI for more intrusive hiring practices are related to higher perceptions of innovativeness and attractiveness. Overall, our findings contribute to our understanding of whether and how using AI in hiring practices contribute the importance of understanding ethical perceptions of using AI in the study of organizational attractiveness.

Theoretical Implications

Our paper has several theoretical implications that are worthy of discussion. We highlight the critical role of incorporating an ethics lens in the organizational attractiveness literature (e.g., Chapman et al., 2005; Highhouse et al., 2003) by highlighting the growing importance of AI ethics in today's human resource management (Vrontis et al., 2022) and the study of what attracts people to organizations (Ehrhart & Ziegert, 2005). Specifically, our findings suggest that one way in which individuals are attracted (or not) to an organization is through the ethical perceptions they hold about the organization's use of AI in their hiring practices. We note, however, that our results also suggest that only individuals who perceive that using AI in hiring is ethical will be attracted to the organizations that use AI in hiring, while those who perceive that using AI in hiring is not ethical will not be attracted to such organizations. Future research could investigate whether and how other aspects of using AI in hiring might contribute to an applicant perceiving the organization as attractive.

Our paper also extends the small but growing literature on AI ethics in HR practices (Pan et al., 2022; Tambe et al., 2019; Vrontis et al., 2022). Specifically, while ethics and organizational attractiveness and innovativeness have been studied together (e.g., Belinda et al., 2018; Riivari & Lämsä, 2019), we found that ethical perceptions pertaining to using AI across various hiring practices are positively related to perceptions of attractiveness and innovativeness for those organizations that use AI in hiring. Interestingly, we also found that these ethical perceptions are not equal across different types of hiring methods. Indeed, we found that ethical perceptions matter most in terms of innovativeness and attractiveness when AI is used for hiring methods that are more intrusive, such as when AI is used to analyze video or audio of applicants for nonverbal behaviors and voice cues. We suggest that this is likely to be due to intrusive practices being more congruent with innovativeness. While our results are consistent across both studies, we encourage future research to further investigate whether and how ethical perceptions of using AI across different types of HR practices are likely to have differing effects on applicants' perceptions of organizational attractiveness. For example, ethical perceptions of using AI in HR practices that are less job-related for applicants (i.e., not directly related to the job content) might be less likely to relate to an applicant perceiving the organization as attractive, compared to ethical perceptions of more job-related HR practices. Another explanation could be that perceptions of attractiveness are more sensitive to ethical concerns for the more intrusive practices (e.g., AI analyzing video of applicants for nonverbal behaviors). Future research could investigate what it is about the ethicality of the intrusive hiring methods that is most relevant in terms of attractiveness.

Finally, we contribute to the P-O fit model (Kristof, 1996) and social identity theory (Tajfel & Turner, 1979) by showing that individuals who have higher ethical perceptions about using AI in hiring practices are likely to perceive that organizations that use AI in hiring share similar values to their own, while further identifying with such organizations. Such findings extend the P-O fit model (Kristof, 1996) and social identity theory (Tajfel & Turner, 1979) to incorporate novel aspects about organizations, in this case the use of AI in hiring methods, and to integrate this novel aspect about organizations with the ethical perceptions people hold about using AI in hiring. This is consistent with recent research that studies human-computer interactions from a social identity lens (Edwards et al., 2019). We encourage future research to examine specific aspects of AI ethics in hiring that are likely to influence these perceptions of P-O fit, and with which applicants are likely to identify. For example, it could be that applicants with a technology background are likely to identify with organizations that use more advanced AI techniques (e.g., interview chatbots).

Practical Implications

Our paper has practical implications for applicants and organizations alike. The primary implications for organizations pertain especially as they seek to enhance their applicant attraction by maintaining ethical HR practices in their use of AI in the hiring process. Indeed, our finding that using AI in hiring is related to increased attractiveness among applicants with higher ethical perceptions about these AI practices, provides a new avenue for organizations to attract potential applicants. Furthermore, following our findings in this context, organizations can increase their attractiveness by portraying themselves as being more innovative. While using AI in hiring will not apply equally to all organizations, especially since not all applicants are attuned to AI use, it provides a novel strategy for understanding how to attract applicants who find AI use in the hiring process as, not only ethical, but innovative as well. This has important implications for HR departments who must decide on the most ethical avenue to integrate AI in their various hiring methods, while being mindful of transparency expectations and restricted budgets. Specifically, HR departments are faced with important (and ethical) questions about whether and how to best use AI in hiring. For example, to what extent will AI help them save time and money without affecting the ethicality of the process? What hiring practices can benefit the most from the use of AI? How can AI help make the hiring process more unbiased?

For applicants, our findings highlight the importance of identifying the right fit in the company that matches their ethical compass. As today's workforce grows increasingly technology-savvy, the growing importance of AI is likely to play a key role in perceptions of fit and personal identification with organizations. As such, our findings suggest that, when applicants do not perceive that using AI in hiring is ethical, they are less likely to be attracted by the idea of working for organizations that use AI in hiring, specifically in hiring methods where AI may seem more pervasive. This is likely to be the case when organizations use AI for intrusive hiring methods, such as analyzing applicants' social media. In these cases where applicants have lower ethical perceptions regarding AI use in hiring, it could be useful to identify whether and how AI is used in the organization before choosing a potential employer, and whether the organization takes on an ethical responsibility for their use of AI-enabled tools in HR (Martin & Freeman, 2004).

Limitations

While we carefully designed two studies that build on each other and mitigate certain methodological concerns, our paper also has some limitations. A first limitation relates to our measure of hiring methods. While we reviewed prior research (McCarthy et al., 2017; Ryan & Ployhart, 2000) and adopted the typology developed by Figueroa-Armijos et al. (2022), which proposes 10 items from theory and practice that provide a fairly comprehensive list of hiring methods, we focused on methods that could realistically be performed by AI. Results from both an EFA and a CFA from two different samples provide validity of our measure. A second limitation is that we focused only on ethical perceptions of using AI in hiring. While this is one of the main contributions of our study, we also encourage future research to investigate other aspects of the use of AI in hiring. For example, as mentioned earlier, future research could look at the usefulness and ease of use of AI in hiring and how this affects organizational attractiveness. Along these lines, future research could also look at the influence of ethical perceptions of using AI in hiring on other organizational personality traits, such as organizational competence (Van Hoye et al., 2013) or prestige (Slaughter et al., 2004).

Another limitation of our two studies in this paper is that we collected self-reported data due to our focus on individual perceptions as our focal variables (Podsakoff et al., 2012). Furthermore, while we carefully designed our model and our hypotheses based on theory, and through two studies, we cannot completely rule out reverse causality (i.e., that perceptions of organizational attractiveness may influence ethical perceptions of using AI in hiring). As such, while it is important to understand perceptions surrounding the use of AI as well as perceptions about organizations, we encourage future research to investigate reactions to the actual use of AI in hiring (e.g., interview chatbots, algorithms to compare candidates), as well as the performance of these AI-driven hiring methods compared to traditional hiring methods. This approach would extend our study by showing whether and how the actual use of AI in hiring influences both applicant perceptions and applicant performance in the hiring process.

A final limitation pertains to our samples. Although we collected two separate samples of actual job seekers and employed individuals with hiring experience from different countries on Prolific, and although we replicated our findings across samples, we encourage future research to conduct field studies with other samples that will allow more robust generalization of findings. For example, it would be interesting to have access to one or more organizations that use AI in hiring in one or multiple countries to replicate our findings by surveying applicants involved in the organizational hiring processes.

Conclusion

While AI is becoming increasingly prevalent across contexts, and there is an emergent research stream exploring whether AI-driven practices are ethical or not (Tambe et al., 2019; Telkamp & Anderson, 2022), we know relatively little about how ethical perceptions of AI influence both individuals and the organizations that use it (Figueroa-Armijos et al., 2022). In this paper, we leverage the P-O fit model (Kristof, 1996; Kristof-Brown et al., 2005), social identity theory (Tajfel & Turner, 1979), and the organizational attractiveness literature (Chapman et al., 2005) to explain why ethical perceptions about using AI in hiring can influence applicants' attraction to organizations that use AI in hiring. Across two studies, we find that higher ethical perceptions of using AI in hiring are related to higher perceptions of organizational innovativeness and attractiveness. This is especially true when using AI for intrusive hiring methods. Overall, we advance knowledge around the importance of AI ethics in hiring, as it pertains to ethical perceptions, as well as perceptions of organizational attractiveness and innovativeness.

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Table 1

Factor Loadings for Ethical Perceptions about Using AI in Hiring Methods[6] *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	.810*	.286	-.064
Assessing applicants' characteristics and traits such as intelligence, honesty, and personality	.396	.720*	.187
Conduct applicant interviews	.228	.904*	.073
Select which applicants will be hired	.199	.891*	.095
Analyze social media information for traits and characteristics	.375	-.167	.641*
Analyze interview text (transcribed) for answer quality	.555*	.349	.444
Analyze video of applicants for nonverbal behaviors	.240	.231	.768*
Analyze still images of applicants for facial features	-.062	.043	.849*
Analyze audio of applicants for voice cues	.046	.238	.841*
Analyze submitted documents from applicants	.707*	.349	.279

[6] Following the list developed and tested empirically by Figueroa-Armijos et al. (2022).

Table 2

Study 1 Descriptive Statistics and Correlations

	Variables	*M*	*SD*	1	2	3	4	5	6
1	Organizational Attractiveness	2.86	1.04	***0.93***					
2	Organizational Innovativeness	3.40	0.76	.45*	***0.86***				
3	Ethical Perceptions about Using AI in Hiring	2.65	0.80	.52*	.29*	***0.86***			
4	Gender	0.41	0.49	.09	.00	.01	-		
5	Age	35.60	12.29	-.19*	-.10	-.06	.02	-	
6	Highest Education	3.77	0.92	-.05	.06	.01	-.07	.10	-
7	Hiring Experience	1.10	1.30	-.02	.07	-.05	-.05	.54*	.05

Note. N = 305. * $p < .05$. 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.

Table 3

Factors Loadings for Measurement Models for Study 1 and Study 2

Factors	Items	Study 1	Study 2
Ethical Perceptions about Using AI in Hiring	Archival Hiring Methods	0.85	0.78
	Hurdle-Process Hiring Methods	0.84	0.8
	Intrusive Hiring Methods	0.82	0.93
Organizational Attractiveness	For me, this company would be a good place to work	0.88	0.92
	I would not be interested in this company except as a last resort (reversed)	0.82	0.72
	This company is attractive to me as a place for employment	0.91	0.9
	I am interested in learning more about this company	0.76	0.79
	A job a this company is very appealing to me	0.91	0.91
Organizational Innovativeness	Interesting	0.74	0.76
	Exciting	0.8	0.74
	Unique	0.73	0.62
	Creative	0.81	0.78
	Boring (reversed)	0.67	0.77
	Plain (reversed)	0.5	0.6
	Original	0.57	0.46

Table 4

Study 1 Standardized Regression Coefficients for Structural Equation Model

Variables	AI Condition					
	Direct Effects			Indirect Effects		
	β	SE	*p*	β	SE	*p*
Organizational Attractiveness						
Organizational Innovativeness	.33*	.05	.000			
Ethical Perceptions about Using AI in Hiring	.47*	.05	.000	.28*	.07	.000
Gender	.08	.05	.087			
Age (log)	-.09	.06	.134			
Highest Education	-.05	.05	.268			
Hiring Experience	-.03	.06	.624			
Organizational Innovativeness						
Ethical Perceptions about Using AI in Hiring	.38*	.06	.000			

Note. N = 305. * $p < .001$.

Table 5

Study 2 Descriptive Statistics and Correlations

	Variables	*M*	*SD*	1	2	3	4	5	6
1	Organizational Attractiveness (T2)	3.10	1.02	***0.92***					
2	Organizational Innovativeness (T2)	3.46	0.73	.67*	***0.85***				
3	Ethical Perceptions about Using AI in Hiring (T1)	2.83	0.91	.51*	.42*	***0.77***			
4	Gender (T1)	0.36	0.48	-.06	-.04	.00	-		
5	Age (T1)	36.30	11.71	-.14*	-.08	.08	.09	-	
6	Highest Education (T1)	4.50	1.32	-.02	.04	.09	.05	.35*	-
7	Hiring Experience (T1)	2.67	1.17	.10	.12	.20*	-.08	.53*	.35*

Note. T1 N = 280; T2 N = 226. * $p < .05$. 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.

Table 6

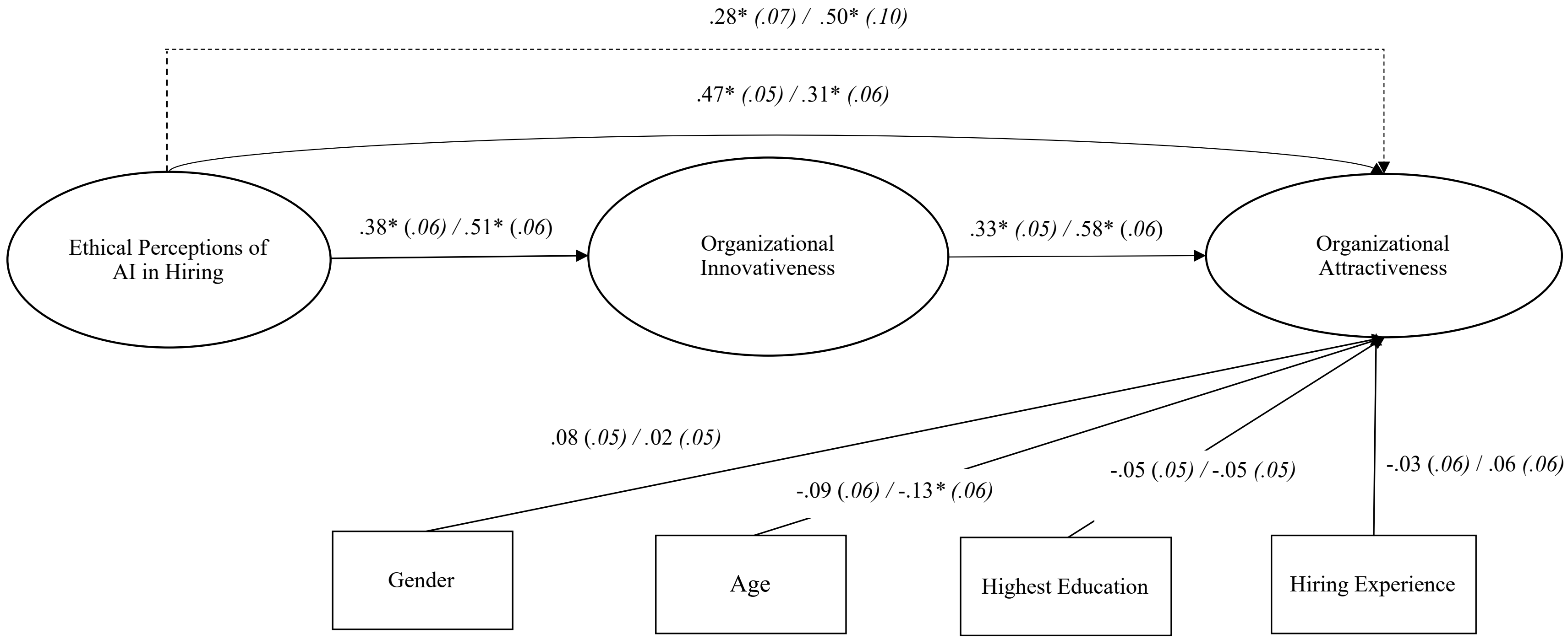
Study 2 Standardized Regression Coefficients for Structural Equation Model

	Direct Effects			Indirect Effects		
	β	SE	*p*	β	SE	*p*
Organizational Attractiveness (T2)						
Organizational Innovativeness (T2)	.58**	.06	.000			
Ethical Perceptions about Using AI in Hiring (T1)	.31**	.06	.000	.50**	.10	.000
Gender (T1)	.02	.05	.721			
Age (log) (T1)	-.13*	.06	.026			
Highest Education (T1)	-.05	.05	.304			
Hiring Experience (T1)	.06	.06	.316			
Organizational Innovativeness (T2)						
Ethical Perceptions about Using AI in Hiring (T1)	.51**	.06	.000			

Note. T1 N = 280 ; T2 N = 226. * $p < .05$, ** $p < .001$

Figure 1

SEM Model and Path Coefficients for Study 1 and Study 2



Note. * p < .05. Standard error in italic between parentheses. Study 1 standardized coefficients on left side of "/" and Study 2 coefficients on right side.

⟶ direct effects

- - - -▸ indirect effects