



Applicant attraction in AI recruitment: The roles of warmth and competence[☆]

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ABSTRACT

Organizations increasingly rely on AI recruitment because it enhances efficiency and signals innovation. However, actual applicant reactions to AI recruitment remain poorly understood. We hypothesize that applicant perceptions of an organization's warmth and competence mediate the effect of AI recruitment on applicant attraction and that applicant technophilia moderates these indirect effects. With five experimental studies (cumulative $N = 2156$ participants), we found consistent support for the warmth pathway but not the competence one. The results evidenced a predominantly negative view of AI recruitment among applicants. Higher technophilia tempered the indirect negative effect of AI recruitment on applicant attraction. These findings call for an extension of human-based recruitment theories, which have thus far failed to adequately address the AI recruitment phenomenon. We show that, as AI usage diffuses, warmth considerations will dominate over competence ones and may lead applicants to eschew organizations when AI recruitment is used. Organizations must recognize that using AI recruitment may be interpreted negatively by applicants, especially by non-technophilic one, and should take action to prevent it from diluting applicant attraction.

1. Introduction

Organizations increasingly rely on artificial intelligence (AI)—machines that simulate human intelligence (von Krogh et al., 2023)—in hiring (Cheng & Hackett, 2021; Shrivastava, 2023; Tambe et al., 2019). AI applications for assessing job candidates and managing the recruitment process (hereafter referred to as *AI recruitment*) are increasingly used in tasks such as evaluating résumés and analyzing video interviews to infer applicants' personality and skills (Chowdhury et al., 2023; Stefanowicz, 2022).¹ Extant research on AI recruitment has primarily adopted an organizational perspective centered on how AI recruitment may boost efficiency through time and cost savings (Chowdhury et al., 2023; Fuller et al., 2021; Mirowska & Mesnet, 2022; Varma et al.,

2023) and signal competence and innovativeness (Black & van Esch, 2020; Stefanowicz, 2022).

Notwithstanding these expected gains, empirical support for the effectiveness of AI recruitment remains elusive (Chowdhury et al., 2023; Pan & Froese, 2023). Although some research suggests that applicants view AI recruitment positively because it signals organizational innovativeness and fairness (Horodyski, 2023; Langer, König, & Papathanasiou, 2019; Ochmann & Laumer, 2020, pp. 1633–1648; van Esch et al., 2019), other research suggests that applicants feel disgruntled with and unfairly treated by organizations using AI recruitment (Hunkenschroer & Luetge, 2022; Langer et al., 2023; Langer, König, Sanchez, & Samadi, 2019). These juxtaposing perspectives leave unclear when and how AI recruitment affects applicant appraisal of and

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¹ AI recruitment still relies on human input and supervision—e.g., in defining evaluation criteria and scrutinizing outputs (Beer et al., 2024), although applicants rarely see this and mostly interact with AI tools.

attraction to an organization. The question is important to address because applicants are a valuable resource that organizations would like to attract (Ployhart et al., 2017; Tang et al., 2022), as shown by organizations' efforts in managing candidate experience (Alden & Harris, 2013; McFarland et al., 2024). Applicant reactions to AI recruitment are critical, as the purported efficiency benefit of AI recruitment would be undermined if applicants exhibit algorithm aversion and eschew the organization, undermining the effectiveness of recruitment (Burton et al., 2020; Dietvorst et al., 2015, 2018; Gee, 2018).

Against this backdrop, we seek to advance the current understanding of applicant reactions and attraction in the context of AI recruitment. Signaling perspectives in recruitment suggest that applicants rely on their perceptions of recruiters, who are often their first point of contact, to infer the organization's "personality" (Rynes et al., 1991; Uggerslev et al., 2012) and inform their attraction to the organization (Chapman et al., 2005; Lievens & Highhouse, 2003; Rynes & Miller, 1983). Warmth and competence are the most prominent signals in this context and significantly influence job applicants' attraction to organizations (Slaughter et al., 2014; Uggerslev et al., 2012). However, we do not know whether these findings based on human recruiters generalize to the context of AI recruitment. Specifically, does recruiter identity as AI (vs. human) impact warmth and competence perceptions and, in turn, applicant attraction? And are these indirect effects moderated by applicants' individual differences?

To address these questions, we integrate the signaling perspective in recruitment with theories of algorithm aversion and appreciation. In line with the algorithm aversion perspective, AI recruitment, when knowable by applicants, may signal lower organizational warmth because AI is seen as artificial and dissimilar to humans, less skilled in recognizing and responding to emotions, and generally lacking humane attributes (Dietvorst et al., 2015; Drummond, 2021; Hong, 2020). At the same time, AI recruitment could be perceived as signaling higher organizational competence due to AI's superior data processing capacity and reduced susceptibility to cognitive biases compared to humans, as suggested by algorithm appreciation (Boyacı et al., 2024; Logg et al., 2019). Moreover, reliance on such a cutting-edge technology may induce mastery appraisals. However, it may also signal lower competence, as AI lacks the common sense necessary for holistic decision-making, potentially producing outcomes that are perceived as unfair (BBC, 2024; Kelan, 2024; Ruttan & Lucas, 2018).

Because both warmth and competence perceptions foster attraction to the organization (Rynes, 1989), the antithetical nature of the proposed indirect effects of AI recruitment on applicant attraction through warmth and competence leaves the overall effect unclear. So, we assess the relative strength of the negative (through both warmth and competence) and positive (through competence) pathways together. Additionally, because relevant individual differences affect how signals such as recruiter characteristics are interpreted (Connelly et al., 2011), we identify applicant trait technophilia—one's general attraction to and frequent usage of technology (Martínez-Córcoles et al., 2017)—as a moderator. Higher technophilia should amplify the positive effect of AI recruitment on competence and attenuate the negative effects on warmth and competence, thus producing a more positive overall impact on applicant attraction. We address our research questions with five studies employing different designs. We find consistent evidence in support of the warmth mechanism, mixed support for the competence mechanism, and clear indication of the moderating role of technophilia.

Our research offers two contributions. First, we advance the development of the applicant reactions perspective in AI recruitment. Specifically, extending the applicant reaction perspective, we identify warmth as a mechanism and applicant technophilia as a critical boundary condition for application reaction to AI recruitment, as more technophilic applicants seem to be less affected by algorithm aversion (Dietvorst et al., 2015, 2018) and appraise AI recruitment relatively more in line with organizations' intentions and goals. Second, we challenge the consensus from human-based recruitment research that

both warmth and competence are key mechanisms linking recruiter characteristics and applicant attraction (Cuddy et al., 2011; Lievens, 2007; Slaughter et al., 2014). We show instead that AI recruitment consistently affects applicant attraction through warmth but not through competence, supporting the "primacy of warmth" perspective (Eisenbruch & Krasnow, 2022) in the context of AI recruitment.

2. Theoretical background and hypotheses

We embrace a broad definition of recruitment, including both recruitment tasks and selection—the identification and measurement of a job applicant's key knowledge, skills, abilities, and other characteristics to inform hiring decisions (Ployhart et al., 2017; Schmitt & Chan, 1998). Because talent is scarce, hard to identify, and challenging to attract (Chamorro-Premuzic et al., 2016; Gee, 2018; Ployhart, 2006), organizations have been increasingly relying on technology in recruitment (Salas et al., 2017). This reliance has evolved beyond the use of traditional, passive web-based tools such as websites (Baum & Kabst, 2014; Kokkodis & Ransbotham, 2023; Williamson et al., 2010), towards the adoption of AI recruitment (Albert, 2019; van Esch et al., 2019). AI is markedly different from earlier recruitment technologies because it functions as a social actor with agentic qualities, capable of partially taking over decision-making processes (Sundar, 2020; van Esch et al., 2019; von der Pütten et al., 2010), marking the advent of the Fourth Industrial Revolution (Schwab, 2017; Tang et al., 2022).

One of the main uses of AI in recruitment relates to the assessment of applicants. AI enables organizations to efficiently screen large applicant pools and filter out unqualified candidates (McCarthy et al., 2017; Suen, 2018), acting as a gatekeeper of sorts (Koren, 2024). AI recruitment supports assessment tasks such as matching candidates and jobs, filtering applicant résumés, juxtaposing an applicant's characteristics with those of successful employees, comparing and selecting candidates based on specific criteria, and making inferences from candidates' facial expressions and body language in recorded interviews (Campion et al., 2016; Cappelli, 2019; Chamorro-Premuzic & Akhtar, 2019; Marr, 2018; Tambe et al., 2019). In most cases, AI performs these and other specific tasks, but does not take over the whole hiring process (Cappelli, 2019; Huang & Rust, 2018; Pan & Froese, 2023). Yet, moving forward, AI will increasingly assist—and sometimes replace—human evaluators in job interviews and assessments, evaluating applicants based on vast data about individual characteristics, achievements, and behaviors (Cheng & Hackett, 2021; Hickman et al., 2022; see also Demirci et al., 2025). Yet, although the time and cost-saving benefits of AI recruitment are evident, its impact on applicant attitudes and attraction to the organization—and, by extension, recruitment effectiveness—remains less understood.

We base our study of applicant reactions to AI recruitment on the extensive research conducted on applicant reactions to human-based recruitment. The literature showed that applicants regard the characteristics of recruiters as representative of the entire organization, and then conceivably build on these characteristics to inform their attraction (or lack thereof) to the organization and their willingness to eventually accept a job offer (Carpentier et al., 2019; Rynes & Miller, 1983; Slaughter et al., 2004; Taylor & Bergmann, 1987; Uggerslev et al., 2012). Indeed, "an outsider's perception of an organization's personality may in fact be a function of his or her perceptions of the personality of a representative of that organization" (Slaughter et al., 2004, p. 86) and, more specifically, "recruiters may influence anticipated job utility because they are viewed by applicants as representative of the nature of the organization itself" (Rynes & Miller, 1983, p. 148). As "impressions of an organization [...] in early recruitment stages are strong predictors of applicants' attraction" (Lievens et al., 2005, p. 554), applicant impressions of the recruiter—often their first point of contact with an organization—are critical. Importantly, past recruitment research aligned with the stereotype content model and identified warmth and competence—universal social cognitions that people assign to social

agents and groups (Fiske et al., 2002, 2007)—as the most critical factors influencing applicant attraction and guiding their job choices (Carpentier et al., 2019; Chapman et al., 2005; Rynes, 1989; Rynes & Miller, 1983; Slaughter et al., 2014). Hence, when applicants perceive a recruiter to be warm and competent, these appraisals will be generalized to represent the whole organization and enhance their attraction to it (Carpentier et al., 2019; Uggerslev et al., 2012).

We study how these universal cognitions extend to the context of AI recruitment. The feasibility of such extension is validated by folk psychology theories and human-machine interaction research, which suggest that people treat artificial agents similarly to how they treat human agents, as long as the artificial agents exhibit social cues (de Graaf & Malle, 2019; Gray et al., 2024; Nass & Moon, 2000; von der Pütten et al., 2010). To assess the directionality of the effects of AI recruitment on organizational warmth and competence perceptions, we integrate human-based recruitment research with recent findings about people's reaction to AI.

2.1. The warmth pathway

People tend to perceive that machines lack humane attributes, such as compassion, empathy, common sense, emotional intelligence, social skills, and moral standards, which leads them to experience algorithm aversion (Dietvorst et al., 2015; Grove & Meehl, 1996; Heer, 2019; Ruttan & Lucas, 2018). Thus, when interacting with artificial agents, applicants perceive them as purely rational and incapable of feeling emotions or understanding abstract ideas. Consequently, applicants assign less warmth to an artificial agent than to a human agent (Sundar, 2020), and so would perceive an AI recruiter as less warm than a human one. Extending their perceptions of recruiters to the whole organization (Carpentier et al., 2019; Uggerslev et al., 2012), applicants will then perceive organizations using AI recruitment to be less warm compared to those purely relying on human-based recruitment. Moreover, as assigning recruitment tasks to AI may be perceived as outsourcing, applicants may interpret AI recruitment as a signal that the organization does not care much for them (Wehner et al., 2015), further lowering perceptions of organizational warmth. As warmth is a desirable characteristic, lower warmth should then decrease applicant attraction to the organization (Carpentier et al., 2019; Rynes, 1989).

Hypothesis 1. AI (vs. human-based) recruitment has a negative indirect effect on applicant attraction through lower perceived organizational warmth.

2.2. The competence pathway

On the one hand, individuals hold favorable attitudes towards AI in some respects. For example, in the context of decision-making people may favor AI-made decisions because AI is less affected by cognitive biases and has a higher capacity to process large amounts of information than humans do (Boyacı et al., 2024; De Véricourt & Gurkan, 2023; Ruttan & Lucas, 2018). So, AI is often considered more competent than humans due to its objectivity and superior data processing capabilities (Dijkstra et al., 1998; Hou & Jung, 2021). Hence, AI should be deemed better able to screen and select applicants because it has fewer cognitive capacity constraints and is less likely than humans to fall into the trap of cognitive biases. Moreover, the organizational perspective suggests that using AI recruitment should enhance applicant perceptions of the organization's competence and innovativeness (Black & van Esch, 2020; da Motta Veiga et al., 2023; Stefanowicz, 2022). So, organizations that use AI recruitment should be appraised as more competent than those that do not. Because competence is a desirable attribute, this should increase applicant attraction to the organization (Chapman et al., 2005; Rynes & Miller, 1983).

Hypothesis 2a. AI (vs. human-based) recruitment has a positive indirect effect on applicant attraction through higher perceived

organizational competence.

On the other hand, AI's ability to process information with less bias does not necessarily ensure that the decision outcomes will be fair. Due to AI's lack of common sense, the backward-looking nature of algorithms (Tambe et al., 2019), and users' limited understanding of the "black box" processes that AI employs to translate inputs into outputs, applicants may perceive AI-made decisions as inferior. For example, AI's decisions may replicate or even amplify biases embedded in the input data—biases that might be detected more readily by human sensitivity than by AI performativity. This issue was illustrated by Amazon's algorithm, which unintentionally learned to discriminate against female job applicants (Rai, 2020). AI may also reflect developers' stereotypes and beliefs, ultimately favoring certain categories of users over others (Kelan, 2024; Magni et al., 2024; Zhang & Hußmann, 2021). Furthermore, candidates may believe that AI (vs. human recruiters) is less capable of assessing them fairly and holistically (e.g., accounting for personal characteristics and hardly quantifiable attributes) and rather suffer from algorithmic reductionism (Lambrecht & Tucker, 2019; Newman et al., 2020; Ruttan & Lucas, 2018). As a result, applicants may perceive organizations that use AI in recruitment as less competent than those that do not. Hence, we advance a competing hypothesis about the directionality of the effect through competence.

Hypothesis 2b. AI (vs. human-based) recruitment has a negative indirect effect on applicant attraction through lower perceived organizational competence.

2.3. The moderation of technophilia

As AI recruitment is expected to have both negative and positive indirect effects on applicant attraction through perceptions of warmth and competence, we aim not only to assess the relative strength of these pathways but also to identify a moderator that might sway the overall indirect effect. Relevant individual differences influence the meaning and strength that receivers (i.e., applicants) assign to a given signal (i.e., AI recruitment), ultimately affecting their psychological experiences and appraisals during recruitment (Connelly et al., 2011; Dineen et al., 2022). In line with our context, we investigate individual differences related to applicants' relationship with technology. In human-AI interaction scenarios, individuals' mental frameworks, attitudes, and heuristics are influenced by their past interactions with artificial agents and their level of digital literacy (Dietvorst et al., 2018; Sundar, 2015, 2020). So, we examine applicant technophilia—a stable trait that reflects a strong attraction to and tendency to use technology (Martínez-Córcoles et al., 2017)—as a moderator of the indirect effects of AI recruitment on applicant attraction.

Individuals higher in technophilia tend to interact more frequently with and be more dependent on technology, to the point of prioritizing interactions with technology over real life occurrences (Martínez-Córcoles et al., 2017; Venkatesh et al., 2019). This frequent usage of technology not only boosts their digital literacy, but also leads them to experience a reduced need for interpersonal interactions and for the affective exchange that characterizes these interactions (Glikson & Woolley, 2020; Krämer et al., 2018; Thomée et al., 2007). Specifically, abundant usage of technological devices can reduce the ability to generate authentic emotional connections by reducing psychological availability (Roberts & David, 2017) and to interfere with the creation of meaningful interpersonal experiences (Sbarra et al., 2019). Relatedly, social interactions occurring with or via technological tools and digital platforms in substitution of in-person interactions can impair social functioning skills and emotional intelligence, for instance through reduced exposure to emotional complexity and through emotional flattening (Abi-Jaoude et al., 2020; Colbert et al., 2016; Uhls et al., 2014). The lower interest in and ability to manage the affective sphere imply that technophiles pay less attention to warmth. Thus, they would perceive a relatively smaller difference in warmth between AI and

human recruitment simply because warmth is not as salient to them. On the contrary, those with low technophilia are more sensitive to the affective side and hence more likely to magnify any warmth perception differences between kinds of social agents, thus associating AI recruitment more negatively with warmth.

In addition, technophiles—by definition—love technology and thus tend to make more positive attributions to artificial agents (e.g., AI) than technophobes do (Martínez-Córcoles et al., 2017). Their enthusiasm about and attraction to AI impact their appraisals, leading them to be less likely to see an AI recruiter as colder than a human one. Ultimately, technophiles hold more favorable views of artificial agents' ability to perform tasks that typically require human intelligence. Technophobes, on the other hand, have less trust in technology and experience a greater feeling of unexpectedness and eeriness as well as fear and anxiety—all antithetical proxies of warmth—when interacting with intelligent artificial agents (Glikson & Woolley, 2020; Khasawneh, 2018; Komiak & Benbasat, 2006; Lee & Wan, 2010). Taking together this less negative perception of technology with a generally lower concern for the affective sphere, we posit the following:

Hypothesis 3. AI (vs. human-based) recruitment has a weaker negative indirect effect on applicant attraction through lower perceived organizational warmth when applicant technophilia is higher rather than lower.

Further, individuals' knowledge of AI's potential thanks to their higher digital literacy and their familiarity with AI's abilities owing to an intense usage of technology—a facet of technophilia—should mitigate concerns about the reliability of AI and thus increase trust in it and appreciation of organizations using it (Fenneman et al., 2021). Indeed, AI literacy and familiarity, and positive inclinations towards AI—constructs theoretically aligned with technophilia—lead people to appraise AI usage more positively (Gillespie et al., 2025). Moreover, higher digital literacy boosts calibration: More digitally literate individuals know better what they can and cannot expect from AI agents, and thus are less likely to hold unreasonable expectations about their performance (Glikson & Woolley, 2020; He et al., 2023).

Higher technophilia is also associated with perceptions of higher fairness and competence in AI decision-making (Glikson & Woolley, 2020; Logg et al., 2019)—an important consideration in recruitment (Varma et al., 2023). Hence, technophiles are more likely to deem AI's decision-making as unbiased and fair and thus to appraise AI as more competent (Glikson & Woolley, 2020; Ochmann & Laumer, 2019). In other words, because technophiles are more digitally literate and positively inclined towards the capabilities of artificial agents—such as the capacity to make more unbiased decisions—they are more likely to deem AI decision makers (and organizations relying on them) as competent.

Moreover, technophiles favor rational logic and interactions with artificial agents over interpersonal interactions (Dineen et al., 2004; Komiak & Benbasat, 2006). Their preference for the rational and logical sphere over the affective one has a double effect. First, technophiles are less likely to deem an artificial agent less competent because of its inferior skill in assessing the emotional component of a human job candidate, simply because such component is of less concern to them. Second, higher technophilia should amplify favorable assessments of competence when an organization uses AI recruitment, because technophiles place a higher emphasis on rational decision-making—a domain where AI is perceived to outperform humans. Furthermore, technophiles value reliance on cutting-edge technology, which should further magnify their interpretation of AI recruitment as a signal of competence. So, higher technophilia should amplify the positive (or weaken the negative) impact of AI recruitment on perceived organizational competence and, in turn, on applicant attraction.

Hypothesis 4. AI (vs. human-based) recruitment has a more positive indirect effect on applicant attraction through higher perceived

organizational competence when applicant technophilia is higher rather than lower.

3. Overview of the studies and transparency statement

To test our hypotheses, we conducted a series of studies. In Study 1, using a between-person design, we tested the mediation hypotheses on a sample of business school students. In Study 2, recruiting a different sample from the same population, we adopted a within-person design, which enabled us to reduce the likelihood that a real difference between the two conditions would remain undetected because of random noise (Price et al., 2015; Whitley, 1996). We also included a proxy measure of technophilia to provide a primary test of the moderation hypotheses. In Studies 3, 4, and 5 we recruited samples of adult workers from USA and tested all hypotheses. In Study 3 we used the same within-person design as in Study 2. In Study 4, we used a between-person design different from that of Study 1 and further tested whether the effects would generalize across hiring stages. Finally, to extend the external validity of our findings, in Study 5 we recruited online platform gig workers using a realistic recruitment scenario.

In all studies, we adhered to the current methodological practices in the field, and all participants gave their informed consent for inclusion before participating. Research materials, experiment rundowns, data, code, results, as well as an online supplement featuring correlation tables, additional analyses, results removing participants who failed attention checks,² and effect sizes, are available on the Open Science Framework repository at <https://bit.ly/aireccdata>, and pre-registrations of the studies at the following links: Study 1: <https://bit.ly/3f0jzca>; Study 2: <https://bit.ly/3VYIgp0>; Study 3: <https://bit.ly/3oi5viD>; Study 4: <https://bit.ly/42OMIA1>; Study 5: <https://bit.ly/4gTPfdy>.

4. Study 1

4.1. Methods

We recruited 305 students (61% female, $M_{age} = 19.00$ years, $SD_{age} = 1.15$) from the business school of a Hong Kong university to participate in the experiment in exchange for course credit. These students were an appropriate subject pool of job applicants because they were in the process of applying for internships as part of their degree. Participants were presented with a scenario where a friend was applying for a job at a company that they themselves were also considering for an internship. They were told that their friend had been invited for a video call with the recruitment manager and that, prior to the video call, the friend had a 10-min web chat with a recruiter. Participants were shown a sped-up video recording of the web chat (available at: <https://vimeo.com/399738269>). Half were told that the recruiter was an AI system (AI condition), and the other half that the recruiter was an HR assistant (human condition). Afterwards, participants rated the organization's warmth and competence, their attraction to the organization, and their own openness, agreeableness, and neuroticism.

All measures were rated by participants on a 7-point agreement Likert scale. Participants rated their perception of the organization as “warm,” “likeable,” and “friendly” for warmth (Cronbach's $\alpha = 0.91$) and “competent,” “intelligent,” and “skilled,” for competence (Cronbach's $\alpha = 0.90$) with commonly used scales (Cuddy et al., 2011; Leach et al., 2007). Participants rated their attraction to the organization with Judge and Cable's (1997) 3-item scale (Cronbach's $\alpha = 0.83$). We included openness, agreeableness, and neuroticism as control variables, because these three have been identified as most predictive of applicant perceptions of organizations (Truxillo et al., 2006). We measured these three control variables with 4-item scales from Donnellan and

² All significance patterns remain consistent when removing participants who failed attention checks.

colleagues (2006) (Cronbach's $\alpha = 0.79$, $\alpha = 0.81$, $\alpha = 0.84$, respectively). We also controlled for participants' age and gender, as older and female individuals may have more negative views of technology and thus relatively prefer humans to AI (Chen & Chan, 2011; Grint & Gill, 2018).

Using SPSS Process macro, we conducted mediation analyses with 5000 bootstrap resamples to generate 95% confidence intervals (CI) to test the hypotheses (Preacher & Selig, 2012). We tested the relative magnitude of the two mediating paths by examining the overall indirect effect of recruiter identity on attraction through warmth and competence together.

4.2. Results and discussion

The regression results are shown in Table 1. AI recruitment had a negative effect on warmth ($b = -.24$, $p = 0.048$) and a positive effect on competence ($b = .30$, $p = 0.009$); both warmth and competence were positively related to attraction to the organization ($b = .39$, $p < 0.001$ and $b = .24$, $p < 0.001$). Hypotheses 1 and 2a were supported, as perceived warmth mediated the negative impact of AI recruitment on applicant attraction (bootstrapped $b = -.09$, CI: $[-.186, -.002]$), while competence positively mediated it (bootstrapped $b = .07$, CI: $[-.019, .135]$). Neither path was dominant, as the overall indirect effect of AI recruitment on applicant attraction—taking together the mediation indices of the warmth and competence pathways—was not significant (bootstrapped $b = -.02$, CI: $[-.150, .108]$).

5. Study 2

5.1. Methods

We recruited 450 business students from a Hong Kong university (56% female, $M_{age} = 19.37$ years, $SD_{age} = 1.28$). Participants saw a recruiting scenario with two fictional LinkedIn job posts from two comparable organizations operating in the tech industry (GateCyan and CrimsonDoor). The organization names and logos were created with the help of AI-based tools (<https://namelix.com> and <https://brandmark.io>). The order of presentation was randomized, as was recruiter identity (AI vs. human). Thus, half participants were told that GateCyan assessed applicants with AI and CrimsonDoor with an HR assistant (CyanAI = 1), and the other half that GateCyan assessed applicants with an HR

Table 1
Hierarchical regression results – study 1.

Variables	Warmth		Competence		Organization Attraction	
	b	SE	b	SE	b	SE
Age	.05	.05	-.02	.05	-.03	.04
Gender	.22	.12	-.03	.12	.11	.09
Openness	-.05	.06	-.06	.06	.05	.04
Agreeableness	.23**	.07	.18**	.07	.05	.05
Neuroticism	.03	.05	.00	.05	-.03	.04
AI Recruitment	-.24*	.12	.30**	.11	-.00	.09
Warmth	—	—	—	—	.39***	.05
Competence	—	—	—	—	.24***	.05

Notes: $n = 305$; Gender: Male = 0, Female = 1. Unstandardized coefficients are reported.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

assistant and CrimsonDoor with AI (CyanAI = 0) to avoid conflating eventual perceived differences between the two organizations.³

For each company, participants rated warmth ($\alpha = 0.93$), competence ($\alpha = 0.89$) and attraction ($\alpha = 0.88$) on the same scales as in Study 1. We further used three items adapted from Melick (2020) to assess the attitudinal facet of technophilia (a sample, reverse-coded item was as follows: “College admissions decisions based on the judgments of an admissions committee are preferable to decisions based on mathematical formulas designed to predict success in college.”). We selected these items from the overall scale because they pertain to the employment domain and are relevant to the context of recruitment.⁴ We reverse coded the items (Cronbach's $\alpha = 0.63$), such that a higher value on the scale indicated higher technophilia.⁵ Finally, they reported their demographics and other controls, as well as attitudinal technophilia, which we used as a proxy to provide a preliminary test of Hypotheses 3 and 4.

To test the hypotheses, we estimated on MPLus (Muthén & Muthén, 2016) 5000-bootstrap confidence intervals with a multi-level analysis, as observations were nested within individuals. The reporting of the results is based on models including age and gender as control variables. We again tested the relative magnitude of the two mediating paths by examining the overall indirect effect of recruiter identity on attraction through warmth and competence together.

5.2. Results and discussion

The regression results are shown in Table 2. AI recruitment had a negative effect on warmth ($b = -.72$, $p < 0.001$) and a positive effect on competence ($b = .24$, $p < 0.001$); both warmth and competence were positively related to attraction to the organization ($b = .45$, $p < 0.001$ and $b = .23$, $p < 0.001$). Accordingly, both warmth (bootstrapped $b = -.32$, CI: $[-.406, -.240]$) and competence (bootstrapped $b = .06$, CI: $[-.028, .082]$) mediated the effect of recruiter identity on attraction, supporting Hypotheses 1 and 2a. The overall indirect effect was negative (bootstrapped $b = -.27$, CI: $[-.358, -.178]$), suggesting the dominance of warmth.

Technophilia moderated the effect of recruiter identity on warmth ($b = .29$, $p < 0.001$), as well as the mediation pathway through warmth (bootstrapped $b = .13$, $SE = .03$, CI: $[-.063, .195]$). Hypothesis 3 was thus supported. Specifically, the mediated effect was negative when technophilia was low (1 SD below the mean) and high (1 SD above the mean), but it was stronger in the former (bootstrapped $b = -.44$, $SE = .06$, CI: $[-.554, -.318]$) than in the latter case (bootstrapped $b = -.20$, $SE = .04$, CI: $[-.283, -.124]$). Hypothesis 4 did not receive support: Technophilia did not moderate the effect of recruiter identity on competence ($b = .07$, $p = 0.21$) nor the mediation pathway through competence (bootstrapped $b = .02$, $SE = .01$, CI: $[-.011, .044]$). The mediated effect was positive when technophilia was either low (bootstrapped $b = .04$, $SE = .02$, CI: $[-.005, .077]$) or high (bootstrapped $b = .07$, $SE = .02$, CI: $[-.033, .109]$), with no significant difference between the two. The overall indirect effect was moderated by technophilia ($b = .15$, $SE = .04$, CI: $[-.071, .220]$).

We note that the measure for technophilia in Study 2 was a proxy, as it was originally intended to measure algorithm aversion. Hence, in

³ We further tested whether the GateCyan and CrimsonDoor were perceived as comparable and found that they did not differ significantly in organization attraction ($F(1, 501) = .04$, $p = 0.833$), warmth ($F(1, 501) = .22$, $p = 0.641$), or job choice ($F(1, 501) = .04$, $p = 0.840$). The only difference was that GateCyan was perceived as more competent than CrimsonDoor ($F(1, 501) = 9.00$, $p = 0.003$).

⁴ The other items in the scale refer to sports management and medical diagnoses and were deemed them irrelevant.

⁵ Because the first item was not strongly correlated with the other two, we also conducted all the analyses—available upon request—with the other two items only ($r = .81$). The significance patterns remained unchanged.

Table 2
Multilevel regression results (study 2).

Variables	Warmth				Competence				Organization Attraction							
	Model 1		Model 2		Model 3		Model 4		Model 5		Model 6		Model 7			
	b	SE	b	SE	b	SE	b	SE	b	SE	b	SE	b	SE		
Age	-.00	.03	-.01	.03	-.02	.03	-.03	.03	-.07	.04	-.06	.03	-.06	.03		
Gender	.07	.07	.07	.07	.08	.08	.07	.08	-.12	.09	-.18*	.07	-.17*	.07		
CyanAI	-.01	.07	-.02	.06	-.03	.08	-.04	.08	.00	.09	.01	.07	.01	.07		
AI Recruitment (AIR)	-.72***	.07	-1.50***	.23	.24***	.05	.05	.17	-.30***	.05	-.03	.05	-.32*	.14		
Warmth	—	—	—	—	—	—	—	—	—	—	.45***	.03	.45***	.03		
Competence	—	—	—	—	—	—	—	—	—	—	.23***	.04	.23***	.04		
Technophilia	—	—	-.30***	.05	—	—	-.22***	.05	—	—	—	—	-.03	.05		
AIR × Technophilia	—	—	.29***	.07	—	—	.07	.06	—	—	—	—	.11*	.05		

Notes: $n = 900$; Gender: Male = 0, Female = 1; CyanAI: GateCyan recruits with a human = 0, GateCyan recruits with an AI = 1. Unstandardized coefficients are reported.

* $p < 0.05$.

** $p < 0.01$.

*** $p < 0.001$.

Study 3, we use a more conceptually precise validated scale to measure technophilia and assess its moderating effects.

6. Study 3

6.1. Methods

In Study 3 we used the same design and analytical strategy as in Study 2. We recruited 505 American adult workers (44% female, $M_{age} = 39.79$ years, $SD_{age} = 11.76$) on Prolific Academic (Palan & Schitter, 2018). Participants were paid GBP 1.5 for completing the experiment. Warmth ($\alpha = 0.95$), competence ($\alpha = 0.94$), and attraction ($\alpha = 0.92$) were measured as in the previous studies. We measured technophilia with Martínez-Córcoles et al.'s (2017) 18-item scale (Cronbach's $\alpha = 0.89$; sample items include “I enjoy using new equipment or technology”; and “I believe that new technology improves life”). We controlled for age, gender, openness ($\alpha = 0.79$), agreeableness ($\alpha = 0.89$), and neuroticism ($\alpha = 0.89$)—measured as in Study 1—and education, as commonly done in studies on attitudes towards AI (Logg et al., 2019).

6.2. Results and discussion

The regression results are shown in Table 3. AI recruitment had a negative effect on both warmth ($b = -1.16$, $p < 0.001$) and competence ($b = -.46$, $p < 0.001$), both of which positively related to attraction to

the organization ($b = .46$, $p < 0.001$ and $b = .42$, $p < 0.001$, respectively). Warmth mediated the effect of AI recruitment on attraction (bootstrapped $b = -.54$, CI: $[-.646, -.438]$), in support of Hypothesis 1. Competence also negatively mediated the effect (bootstrapped $b = -.20$, CI: $[-.251, -.140]$), supporting Hypothesis 2b and in opposition to the results from previous studies. The overall indirect effect of AI recruitment on attraction was negative (bootstrapped $b = -.74$, CI: $[-.848, -.627]$).

Technophilia moderated the effect of recruiter identity on warmth ($b = .18$, $p = 0.005$). The mediated effect was negative both when technophilia was low (1 SD below the mean) (bootstrapped $b = -.60$, CI: $[-.718, -.479]$) and when it was high (1 SD above the mean) (bootstrapped $b = -.45$, CI: $[-.561, -.338]$), but it was stronger in the former than in the latter case (bootstrapped $b = .08$, CI: $[.024, .138]$), hence supporting Hypothesis 3. Technophilia did not moderate the effect of AI recruitment on competence ($b = .11$, $p = 0.053$). Accordingly, the pathway through competence was negative both when technophilia was low (bootstrapped $b = -.23$, CI: $[-.311, -.156]$) and high (bootstrapped $b = -.15$, CI: $[-.212, -.087]$) and the two were not different (bootstrapped $b = .08$, CI: $[-.002, .094]$), not supporting Hypothesis 4.

Table 3
Multilevel regression results – study 3.

Variables	Warmth				Competence				Organization Attraction							
	Model 1		Model 2		Model 3		Model 4		Model 5		Model 6		Model 7			
	b	SE	b	SE	b	SE	b	SE	b	SE	b	SE	b	SE		
Age	.01	.00	.01	.00	.01	.00	.01	.00	.01**	.00	.01**	.00	.01**	.00		
Gender	.21*	.09	.21*	.09	.14	.08	.14	.08	.02	.09	-.14*	.06	-.14*	.06		
Education	-.09	.05	-.09	.05	-.07	.05	-.07	.05	-.05	.06	.02	.04	.02	.04		
Openness	-.09**	.03	-.09**	.03	-.03	.03	-.03	.03	-.06	.04	-.01	.03	-.01	.03		
Agreeableness	.11**	.04	.11**	.04	.09*	.04	.09*	.04	.06	.04	-.03	.03	-.03	.03		
Neuroticism	-.08**	.03	-.08**	.03	-.07**	.03	-.07**	.03	-.09**	.03	-.02	.02	-.02	.02		
CyanAI	-.11	.08	-.11	.08	-.04	.07	-.04	.07	-.03	.08	-.03	.06	.03	.06		
AI Recruitment (AIR)	-1.16***	.06	-1.93***	.28	-.46***	.05	-.92***	.25	-.97***	.06	-.23***	.05	-.83***	.24		
Technophilia	.42***	.05	.33***	.06	.33***	.05	.28***	.04	.40***	.06	.07*	.03	.00	.04		
AIR × Technophilia	—	—	.18**	.06	—	—	.11	.06	—	—	—	—	.14**	.05		
Warmth	—	—	—	—	—	—	—	—	—	—	.46***	.04	.45***	.04		
Competence	—	—	—	—	—	—	—	—	—	—	.42***	.04	.42***	.04		

Notes: $n = 1010$; Gender: Male = 0, Female = 1; Education: Primary school or lower = 1, Secondary school = 2, Bachelor diploma = 3, Postgraduate diploma = 4; CyanAI: GateCyan recruits with a human = 0, GateCyan recruits with an AI = 1. Unstandardized coefficients are reported.

* $p < 0.05$.

** $p < 0.01$.

*** $p < 0.001$.

7. Study 4

7.1. Methods

In Study 4 we sought not only to replicate the findings, but also to test whether the effects would generalize across stages of the hiring process such as initial screening and final selection. On Prolific, we recruited 600 adult American workers (34% female and 1% non-binary, $M_{age} = 39.18$ years, $SD_{age} = 13.10$), who were paid GBP 1.5 for completing the experiment. We used a 2×2 between-person design, manipulating recruiter identity (AI vs. human) and hiring process stage (initial prescreening vs. final selection).

We asked participants to report their technophilia first to ensure that the manipulation did not influence the moderator. Then, we showed participants a recruitment scenario: They received an email from GateCyan that invited them to an interview and told them that they would have to write a short self-presentation essay. Depending on the condition, participants were told that the essay and interview would be assessed by an AI system or by a hiring manager, and that the interview was either an initial recruitment interview (prescreening stage) or a final selection interview (selection stage). Afterwards, they reported their perceptions of GateCyan's warmth and competence, followed by their attraction to it, the control variables, and demographics.

Warmth ($\alpha = 0.93$), competence ($\alpha = 0.92$), organization attraction ($\alpha = 0.89$), and technophilia ($\alpha = 0.89$) were measured with the same scales as Study 3. As in Study 1, we included openness ($\alpha = 0.83$), agreeableness ($\alpha = 0.90$), and neuroticism ($\alpha = 0.88$), as well as age, gender, and education as controls. We also controlled for hiring stage. The analytical strategy mirrored that of Study 1, with the addition of moderated mediation tests. We explored the moderating effect of the hiring stage—reported in the online supplement—and found no significant moderation, supporting the generalizability of results across hiring stages.

7.2. Results and discussion

Regression results are shown in Table 4. AI recruitment had a negative effect on warmth ($b = -.60, p < 0.001$), as well as on competence ($b = -.23, p = 0.003$). Both warmth and competence were positively related to applicant attraction ($b = .40, p < 0.001$ and $b = .40, p < 0.001$). Hypothesis 1 was supported, as warmth mediated the negative impact of AI recruitment on applicant attraction (bootstrapped $b = -.23$, CI: $[-.334, -.144]$). In line with Hypothesis 2b and Study 3,

AI recruitment had a negative indirect effect on applicant attraction through competence (bootstrapped $b = -.09$, CI: $[-.166, -.029]$). The overall indirect effect of AI recruitment on attraction was negative (bootstrapped $b = -.33$, CI: $[-.457, -.201]$).

Technophilia moderated the effect of AI recruitment on warmth ($b = .19, p = 0.048$), as well as on the warmth pathway linking AI recruitment and applicant attraction (bootstrapped $b = .07$, CI: $[.002, .151]$). The effect of AI recruitment was negatively related to applicant attraction through warmth both when technophilia was low and when it was high, but more strongly in the former (bootstrapped $b = -.30$, CI: $[-.434, -.182]$) than in the latter case (bootstrapped $b = -.16$, CI: $[-.280, -.064]$), supporting Hypothesis 3. Technophilia also moderated the direct effect of recruiter identity on competence ($b = .17, p = 0.042$) and the indirect effect on applicants' attraction through competence (bootstrapped $b = .07$, CI: $[.001, .141]$). In support of Hypothesis 4, the mediation through competence was negative at low technophilia (bootstrapped $b = -.16$, CI: $[-.269, -.057]$) and non-significant at high technophilia (bootstrapped $b = -.03$, CI: $[-.117, .049]$).

8. Study 5

8.1. Methods

To provide evidence from a more realistic setting, in Study 5 we tested the hypothesized relationships on actual job seekers: online platform gig workers. Specifically, we recruited a sample of 296 participants (55.74% female and 1% non-binary, $M_{age} = 39.41$ years, $SD_{age} = 13.70$) on Prolific. We presented them with the chance to apply for joining a pool of online behavioral research participants affiliated to an organization (Online Behavioral Lab – OBL). Half participants were told that the application would be assessed by a lab manager, and the other half by an AI algorithm. They completed the study believing that part of it was an application for joining the OBL online pool, and were then debriefed about its fictional nature.

The measures used were the same as in previous studies. Participants first reported their demographics and technophilia ($\alpha = 0.91$). Then, they completed the application, which consisted of two short tasks: reporting three highlights from their CV and evaluating the creativity of previously generated solutions to a problem. After completing the application, they were asked to report OBL's warmth ($\alpha = 0.90$) and competence ($\alpha = 0.93$), and finally their attraction to OBL ($\alpha = 0.82$). The analytical strategy mirrored previous between-person studies.

Table 4
Hierarchical regression results – study 4.

Variables	Warmth				Competence				Organization Attraction					
	Model 1		Model 2		Model 3		Model 4		Model 5		Model 6		Model 7	
	b	SE	b	SE	b	SE	b	SE	b	SE	b	SE	B	SE
Age	.00	.00	.00	.00	.01**	.00	.01	.00	.01	.00	.00	.00	.00	.00
Gender	.08	.10	.09	.10	.04	.08	.05	.08	-.04	.10	-.09	.07	-.09	.07
Education	.03	.06	.03	.06	-.00	.05	.01	.05	.05	.06	.04	.04	.04	.04
Openness	-.04	.04	-.04	.04	.08*	.04	.08	.04	.05	.04	.04	.03	.04	.03
Agreeableness	.27***	.04	.27***	.04	.14***	.04	.15***	.04	.21***	.04	.05	.03	.05	.03
Neuroticism	-.09**	.03	-.09	.03	-.04	.03	-.04	.03	-.04	.03	.01	.02	.01	.02
Hiring Stage	.23**	.09	.23*	.09	.19*	.08	.18*	.08	.52***	.09	.35***	.07	.35***	.07
AI Recruitment (AIR)	-.60***	.09	-1.47**	.45	-.23**	.08	-1.02**	.39	-.45***	.09	-.12	.07	.02	.34
Technophilia	.43***	.05	.33***	.07	.32***	.05	.23***	.06	.36***	.05	.07	.04	.09	.05
AIR $\times$ Technophilia	—	—	.19*	.10	—	—	.17*	.08	—	—	—	—	-.03	.07
Warmth	—	—	—	—	—	—	—	—	—	—	.40***	.04	.39***	.04
Competence	—	—	—	—	—	—	—	—	—	—	.40***	.04	.40***	.05

Notes: $n = 600$; Gender: Male = 0, Female = 1; Education: Primary school or lower = 1, Secondary school = 2, Bachelor diploma = 3, Postgraduate diploma = 4; Hiring Stage: Recruitment = 0, Selection = 1. Unstandardized coefficients are reported.

* $p < 0.05$.

** $p < 0.01$.

*** $p < 0.001$.

8.2. Results

The regression results are shown in Table 5. The effect of AI recruitment was negative on warmth ($b = -.31, p = 0.007$), and non-significant on competence ($b = .01, p = 0.890$). Both warmth and competence were positively related to applicant attraction ($b = .21, p < 0.001$ and $b = .33, p < 0.001$). Hypothesis 1 was supported, as warmth mediated the negative impact of AI recruitment on applicant attraction (bootstrapped $b = -.07$, CI: $[-.126, -.018]$). Hypothesis 2 was instead unsupported, as competence did not mediate the effect of AI recruitment on applicant attraction (bootstrapped $b = .00$, CI: $[-.068, .077]$). The overall indirect effect of AI recruitment on attraction was non-significant (bootstrapped $b = -.06$, CI: $[-.166, .049]$).

Technophilia moderated the effect of AI recruitment on warmth ($b = .35, p = 0.003$), as well as on the warmth pathway linking AI recruitment and applicant attraction (bootstrapped $b = .07$, CI: $[-.021, .147]$). Specifically, the effect of AI recruitment was negatively related to applicant attraction through warmth when technophilia was low (bootstrapped $b = -.14$, CI: $[-.244, -.057]$) but not when it was high (bootstrapped $b = .01$, CI: $[-.059, .086]$), supporting Hypothesis 3. Technophilia also moderated the direct effect of recruiter identity on competence ($b = .39, p < 0.001$) and the indirect effect on applicants' attraction through competence (bootstrapped $b = .13$, CI: $[-.057, .217]$) in line with Hypothesis 4, as the mediation through competence was negative at low technophilia (bootstrapped $b = -.13$, CI: $[-.243, -.024]$) and positive at high technophilia (bootstrapped $b = .13$, CI: $[-.043, .244]$).

9. General discussion

Responding to calls to update organizational research in light of the diffusion of AI in organizations (George et al., 2016; Klein & Cooke, 2022), we examined whether and how findings from human-based recruitment research would extend to AI recruitment. Results from five experimental studies provided consistent evidence that AI recruitment leads applicants to appraise an organization as less warm and, in turn, be less attracted to it. However, AI recruitment did not consistently influence perceptions of an organization's competence. Technophilia mitigated the negative spillover of AI recruitment on perceptions of warmth, whereas its moderation on the competence pathway was less consistent.

9.1. Implications for theory and research

Our research speaks directly to a peculiar tension in recruitment: The increased reliance on AI recruitment goes hand in hand with the need to keep desirable candidates engaged and interested during (and after) the hiring process by creating a positive candidate experience (Alliden &

Harris, 2013; Carpenter, 2013; McFarland et al., 2024). The tension lies in the co-existence of time and cost saving through AI recruitment—which, according to our findings, reduces candidates' attraction—and the costly management of candidate experience—which is a critical driver of attraction (Miles & McCamey, 2018; Van Iddekinge et al., 2023). Our findings about warmth underscore that human touch matters still—and maybe even more—in the age of AI recruitment (see also Tursunbayeva et al., 2025). We therefore urge organizations to pay more attention to applicant attitudes about and reactions to AI usage in recruitment if they wish to reap the benefits of AI (see Malik et al., 2023; Wang et al., 2024). We hereby elaborate on how our key findings extend management research.

9.1.1. A mismatched interpretation of AI recruitment

Whereas organizations strategically implement AI recruitment to increase efficiency and to signal their innovativeness and competence to stakeholders (Black & van Esch, 2020), a specific group of stakeholders—job applicants—tend to react negatively to such signal because of perceptions of lower organizational warmth. Accordingly, our findings challenge the view that AI recruitment primarily engenders perceptions of higher organizational competence and desirability (Black & van Esch, 2020; da Motta Veiga et al., 2023; Ochmann & Laumer, 2020, pp. 1633–1648), rather revealing the dominance of applicants' negative view of AI recruitment. It also resonates with a recent Pew Research Center report, according to which up to two thirds of surveyed Americans would not apply to an organization that uses AI recruitment (Rainie et al., 2023). Hence, neglecting the alienating effect of AI recruitment on applicants in the quest for time and cost saving is sub-optimal, as applicants' lower warmth perception of AI and the ensuing algorithm aversion limits the potential benefits stemming from its utilization (Burton et al., 2020; Dietvorst et al., 2015, 2018) and ultimately prevents efficiency gains from translating into recruitment effectiveness. This organizational myopia may explain why acquiring and managing talent remains a challenge in the Fourth Industrial Revolution. As organizations may overestimate the benefits of AI recruitment, we suggest they adopt a more balanced and holistic outlook on AI recruitment. While we examined applicant reaction, organizations should also integrate recruiters' perspective on AI recruitment (e.g., Horodyski, 2023; Roumbanis, 2025), as considering both perspectives can inform a holistic judgment of its benefits and drawbacks.

We further note that our finding regarding warmth does not necessarily conflict with the use of AI for high-volume recruitment. By saving time thanks to the efficiency gains, using AI paradoxically provides an opportunity to enhance human touch and candidate experience in the case of large volume recruitment—unless the efficiency gains are rather spent to process more applicants. So, organizations should consider investing the saved time in relationship building with applicants to

Table 5
Hierarchical regression results – study 5.

Variables	Warmth				Competence				Organization Attraction					
	Model 1		Model 2		Model 3		Model 4		Model 5		Model 6		Model 7	
	b	SE	b	SE	b	SE	b	SE	b	SE	b	SE	B	SE
Age	-.01	.00	-.01	.00	-.00	.00	-.00	.00	.00	.00	.00	.00	.00	.00
Gender	.11	.10	.11	.11	.32**	.11	.32**	.11	.14	.10	.01	.09	.01	.09
Education	.05	.07	.05	.07	-.07	.07	.01	.06	-.13*	.06	-.11*	.05	-.11*	.05
AI Recruitment (AIR)	-.31**	.11	-1.91***	.54	.01	.11	-1.81**	.50	.03	.10	.09	.08	.01	.41
Technophilia	.51***	.06	.35***	.08	.49***	.06	.31***	.07	.42***	.05	.14**	.05	.09*	.06
AIR × Technophilia	—	—	.35**	.11	—	—	.39***	.11	—	—	—	—	.02	.09
Warmth	—	—	—	—	—	—	—	—	—	—	.21***	.06	.21***	.06
Competence	—	—	—	—	—	—	—	—	—	—	.33***	.06	.33***	.06

Notes: $n = 296$; Gender: Male = 0, Female = 1; Education: Primary school or lower = 1, Secondary school = 2, Bachelor diploma = 3, Postgraduate diploma = 4. Unstandardized coefficients are reported.

* $p < 0.05$.

** $p < 0.01$.

*** $p < 0.001$.

counteract the negative effect on warmth engendered by AI recruitment.

9.1.2. *The nuanced role of competence and the primacy of warmth*

Warmth and competence are established and fundamental mechanisms that explain the influence of recruiters on applicant attraction in traditional human-based hiring processes. When considering the extension of these mechanisms to AI recruitment, we discovered that, whereas warmth consistently plays a significant role, competence can be both enhanced and diminished by AI recruitment. The complex and inconsistent role of competence likely stems from the fact that AI recruitment can engender perceptions of both competence (e.g., evaluation consistency) and incompetence (e.g., less holistic evaluations, reductionism) (see De Véricourt & Gurkan, 2023; Lambrecht & Tucker, 2019; Newman et al., 2020). The Janus-faced nature of competence helps explain why findings about the competence pathway were inconsistent in our studies and thus suggests the need for a theoretical fine-tuning of competence as a driver of people's attitudes in the context of AI recruitment. So, past research on competence may have induced erroneous conclusions and that non-significant findings might have emerged owing to the lack of a more granular assessment of competence that affords capturing its divergent facets and ambivalent pull. Current measures of competence thus need to be fine-grained to acknowledge its different facets.

Another possible explanation for the nuanced findings about competence could be the relative importance of attitudes towards AI decision-making in high-stakes decisions—of which hiring is an example—that carry far-reaching implications for people's life (Tambe et al., 2019). Past research evidenced how people's attitudes towards AI in high-stakes decisions vary depending on the domain and task: In some high-uncertainty domains, such as healthcare and voting behavior prediction, people heed less to AI and discount its competence, whereas the opposite happens in other high-uncertainty domains such as war-like situations or airplane operations (De Véricourt & Gurkan, 2023; Magni et al., 2024; Mahmud et al., 2022; Sarter & Woods, 2017; Sutherland et al., 2016). Further research is needed to identify the specific characteristics of high-stakes situations in organizations—including recruitment—that influence preferences for or against AI.

Interestingly, even when our participants linked AI recruitment to higher competence (e.g., Studies 1 and 2), this did not translate into overall higher attraction, as the positive competence pathway was neutralized or overshadowed by the negative one through warmth. The dominance of the warmth pathway aligns with evolutionary psychology perspectives. One explanation is that warmth is other-profitable (i.e., other people benefit most from a focal actor's warmth) whereas competence is self-profitable (i.e., the self benefits most from one's competence), and thus the former holds more consequence in social interactions (Eisenbruch & Krasnow, 2022). Eisenbruch and Krasnow (2022) further argued that humans have historically experienced higher variance in social counterparts' warmth compared to competence, and thus they used warmth as a more informative cue to determine attitudes and decisions due to its higher variance in the social environment. It appears that such evolutionary perspectives are well-suited to explain interactions with non-human agents as well, in line with theories of human-machine interaction (Nass & Moon, 2000).

9.1.3. *Nuances of the effects of AI recruitment on applicant attraction*

We also contribute to recruitment research by identifying technophilia as a consequential individual difference for how applicants react to AI recruitment. Overall, applicant technophilia emerged as a critical individual difference that cannot be overlooked when studying the effects of AI recruitment. This was most evident in Study 5—the most realistic study—where the effect of AI recruitment on attraction via competence was positive for technophiles and negative for technophobes. However, other relevant boundary conditions may require further study. We focus on two specifically: hiring process stage and demographic differences.

In Study 4 we discovered that our findings held in both the pre-screening and selection conditions, suggesting that the hypothesized effects generalize across hiring process stages. This finding, although it needs to be replicated, contrasts research suggesting that people are more accepting of AI giving advice (e.g., providing HR and hiring managers with information in the applicant screening stage) rather than making important decisions (e.g., deciding which applicant to hire in the selection stage), as they prefer to retain control over decision-making (Alon-Barkat & Busuioc, 2023; Langer & Landers, 2021; Schaap et al., 2024). Perhaps, the level of interaction directness between applicant and recruiter may also moderate the effects we discovered, with stronger effects elicited by more direct interactions (e.g., during interviews).

The cumulative findings across five studies also reveal interesting insights into age and culture as potentially relevant moderators. In Studies 1 and 2 (Hong Kong students), AI recruitment led to higher competence, whereas in other studies (American adults) to lower (Studies 3 and 4) or non-significantly different (Study 5) competence. Hence, age and/or culture differences may drive different competence perceptions of AI recruitment. Regarding age, younger individuals have grown up surrounded by technology and tend to have a more positive inclination towards artificial agents and their capabilities (Stewart et al., 2017). Older people, on the contrary, encounter more difficulty in processing stimuli due to a weakened working memory and, as a result, rely more on subjective norms, which decreases their acceptance of new technology compared to younger individuals (Morris & Venkatesh, 2000). Hence, younger applicants may generally be more positively inclined towards organizations using AI recruitment, and thus be more likely to rate them as relatively more competent. However, one counterpoint to this argument emerged from our data: We found no significant correlation between age and technophilia in any of our studies, nor any consistent moderation by age.

Regarding cultural differences, in 2019 over 94% of households in Hong Kong had access to the Internet compared to 86.6% in the USA, and 91.5% of those older than 10 owned a smartphone in Hong Kong (99.6% in the 15-24 age group) compared to 81% of adults in the USA (Hong Kong Census and Statistics Department, 2020; Pew Research Center, 2021; USA Census Bureau, 2020). In addition, Hong Kong youth have been found to spend more time in front of screens compared to their American counterparts (Ng, 2017). Research also found that Chinese individuals hold more positive perceptions of and trust in artificial agents than Americans do (Liu et al., 2024; World Economic Forum, 2022). These data point to more positive attitudes towards technologies—not fully captured by technophilia—in some cultures (e.g., Hong Kong) than others (e.g., USA). Future research should test to what extent cultural differences in attitudes towards AI and technology may affect reactions to AI recruitment.

9.2. *Practical implications*

Because higher technophilia mitigates negative applicant attitudes towards AI recruitment, as AI recruitment proliferates and applicants become familiar with it, unfavorable attitudes towards it may naturally decline (see Glikson & Woolley, 2020). Organizations can expedite this familiarization process by enhancing applicant pools' knowledge of and enthusiasm for technological advances in general, and AI recruitment in particular. For instance, they could implement AI-recruitment familiarization workshops aimed at university students or employment agency candidate pools. Recruiters could also provide applicants with clear explanations of the benefits of AI recruitment, potentially fostering more favorable perceptions of AI recruitment and the organization (Basch & Melchers, 2019).

Alternatively, when consistent with their needs (e.g., when hiring for tech-heavy positions or in organizations whose mission and values are closely related to cutting-edge technology), organizations can leverage AI recruitment to attract applicants who value efficiency and limited human interaction. These values, signaled by espousing AI recruitment,

can naturally filter out applicants (e.g., technophobes) who may be undesired, helping reduce costs and streamline candidate processing (Campion et al., 2019).

However, the challenge remains: Applicants are generally less attracted to organizations that use AI recruitment because such organizations are perceived as less warm. Lower applicants' interest can seriously hamper organizations' capability to acquire talent. Existing knowledge suggests that organizations use AI recruitment not only to save time and costs, but also strategically to signal innovativeness and competence to applicants. We find this not to be the case, as this perspective is overshadowed by perceptions of low warmth and the ensuing negative reactions. To address this, organizations should proactively manage the adoption of AI recruitment to ensure that they do not alienate applicants. For instance, organizations using AI recruitment should use the saved time to foster relationship building with applicants or by showing care for employees through the offer of well-being packages; see (Dierickx et al., 2024; Walker et al., 2015) to compensate for the adverse effect on warmth of AI recruitment. Doing so is essential to not only reap the efficiency and image benefits AI recruitment can offer, but also to improve applicant experience and reaction (e.g., in terms of warmth perception).

9.3. Limitations

Despite the strengths of our design, our research has limitations. First, our experimental designs were well-suited to testing causality and filtering out external noise, and we also conducted a realistic experiment with Study 5 by making participants believe that they were going through a real application procedure. Nevertheless, complementing these experiments with field surveys would further enhance external validity. We also acknowledge that organizations that use AI recruitment are not necessarily comparable to those that do not, as was instead in our experimental designs. For example, large corporations are more likely to implement AI recruitment because they have more resources and larger applicant pools (Bajaj, 2023). This could introduce confounding factors (e.g., reputation), making rigorous field data collection particularly challenging. Additionally, variations in the AI tools used across organizations and their effectiveness could add further noise. Moreover, our studies were possibly affected by empirical limitations due to design choices. For instance, in Study 4 we measured technophilia before showing participants the manipulation, which may produce demand effects. However, complementing this design choice with the *ex-post* measuring of technophilia in other studies, we find consistent findings and this should strengthen the confidence in empirical support for our moderation hypotheses. Additionally, in Study 5 we could not reliably check whether participants believed in the reality of the scenario before being debriefed.

Second, past research showed that a fit between the employer and third-party service providers can mitigate negative applicant reactions stemming from recruitment outsourcing (Wehner et al., 2015). In our studies, the companies were described as operating in the technology industry and thus exhibiting a good fit with eventual AI recruitment service providers. Despite this alignment, we still found negative applicant reactions to AI recruitment, showing that our findings are relatively conservative and robust. Nonetheless, following this reasoning but switching level of analysis from organization to job, it is possible that AI recruitment may engender a less negative reaction when utilized for jobs that are perceived as more fitting—e.g., a data scientist vs. a public relations executive. Future research may test this potential boundary condition.

9.4. Conclusions

AI recruitment leads organizations to be perceived as less warm, which decreases their attractiveness. This negative effect is mitigated when job applicants have higher technophilia. Organizations using AI

recruitment may be perceived as either more and less competent, with the mixed findings calling for more research on the nuanced role of competence perceptions in driving the relationship between recruiter characteristics and applicant attraction. Organizations should be mindful of the unintended consequences of AI recruitment in their quest to attract talent. To maximize the benefits of AI recruitment, they should devote the saved time to fostering human touch and relationship building with applicants. Alternatively, they could use AI recruitment strategically, for example to filter out applicants with low technophilia.

CRediT authorship contribution statement

Federico Magni: Writing – review & editing, Writing – original draft, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Yaping Gong:** Writing – review & editing, Supervision, Methodology, Investigation, Funding acquisition, Conceptualization.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work, we did not use any GenAI tool to aid the writing process. We used GenAI tools to help prepare some of the experimental materials (e.g., logos of fictional companies). We take full responsibility for the content of the published article.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Federico Magni reports financial support and administrative support were provided by The Hong Kong University of Science and Technology. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.chbr.2026.101169>.

Data availability

Data are available on the OSF repository linked in the manuscript

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