No Thanks, Dear AI! Understanding the Effects of Disclosure and Deployment of Artificial Intelligence in Public Sector Recruitment

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Abstract: Applications based on artificial intelligence (AI) play an increasing role in the public sector and invoke political discussions. Research gaps exist regarding the *disclosure effects*—reactions to disclosure of the use of AI applications—and the *deployment effect*—efficiency gains in data savvy tasks. This study analyzes disclosure effects and explores the deployment of an AI application in a pre-registered field experiment (n=2,000) co-designed with a public organization in the context of employer-driven recruitment. The results show that disclosing the use of the AI application leads to significantly less interest in an offer among job candidates. The explorative analysis of the deployment of the AI application indicates that the person–job fit determined by the leaders can be predicted by the AI application. Based on the literature on algorithm aversion and digital discretion, the study offers a theoretical and empirical disentanglement of the disclosure effect and the deployment effect to support the evaluation of AI applications in the public sector. It contributes to the understanding of how AI applications can shape public policy and management decisions, and discusses the potential benefits and downsides of disclosing and deploying AI applications in the public sector and in employer-driven public sector recruitment.

Keywords: Algorithmic decision-making, algorithm aversion, digital discretion, field experiment, employer-driven recruitment

1 INTRODUCTION

Algorithmic decision-making systems based on artificial intelligence (AI applications) are increasingly adopted in public service provision (Grimmelikhuijsen & Meijer, 2022), for example in the context of policing, criminal justice, or other public services (Vogl et al., 2020). In the workplace, AI applications are used, for instance, to identify and select job candidates (van den Broek et al., 2021) and to evaluate current employees by tracking employees' work using big data analytics to evaluate performance or generate feedback (Tong et al., 2021). They are used more and more in non-routine, high-stakes areas of public service work (Alon-Barkat & Busuioc, 2022). Research increasingly explores how and why they affect decision-making in the public sector (Nagtegaal, 2021). AI applications are described as a "[…] new generation of technologies capable of interacting with the environment by (a) gathering information from outside (including from natural language) or from other computer systems; (b) interpreting this information, recognizing patterns, inducing rules, or predicting events; (c) generating results, answering questions, or giving instructions to other systems; and (d) evaluating the results of their actions and improving their decision systems to achieve specific objectives" (Glikson & Woolley, 2020, p. 631). These technologies apply algorithms, evidence-based formulas or rules, including "statistical models, decision rules, and all other mechanical procedures that can be used for forecasting" (Dietvorst et al., 2015, p. 114).

Public organizations face trade-off situations when adopting AI applications. On the one hand, research has identified several obstacles, for example related to datasets used, and organizational issues such as a lack of skills (Agarwal, 2018). Further challenges, such as the lack of interpretability of some AI applications, have raised questions about accountability, ethics, legitimacy, and trust (Busuioc, 2021). On the other hand, implementing AI applications promises benefits related to efficiency and performance, economic aspects and costs, data and information processing, and decision-making (for a review, see Zuiderwijk et al., 2021). Such trade-offs have not yet been examined sufficiently in academic literature. There is a lack of understanding about the effects of AI applications on decision-making and outcomes in public organizations.

This study analyzes a trade-off situation public organizations face in the context of AI applications: Balance between potentially negative disclosure effects due to negative user reactions and potentially positive deployment effects due to possible efficiency gains in decision-making. The *disclosure effect* describes that individuals react with aversion once the use of AI application is made transparent even if they know that the specific algorithmic forecast is superior to human expert prediction (Dietvorst & Bharti, 2020). The *deployment effect* refers to potential efficiency gains such as relieving public employees from mass transactional duties by automating data-intensive tasks and facilitating informed decision-making. As described in the literature on digital discretion, this can result in fundamental changes in decision-making (Busch & Henriksen, 2018).

In this study, the effects of disclosing and deploying an AI application are tested at the level of individual decision-making in the context of employer-driven recruitment in the public sector. It reports the results of a field experiment piloting the use of an AI application with a public employer. The AI application is used to search for candidates on social media job platforms, compile their information, and assess their person–job fit. The public employer deployed the AI application to identify 2,000 candidates with a basic person–job fit and send a personal message to the candidates. The candidates were randomized into four groups that received the same direct sourcing message including a real job offer, but with different disclosure interventions informing them how they were identified as suitable candidates. Additionally, public leaders of the cooperating employers assessed the person–job fit of 695 randomly chosen candidates independently from the AI application deployed.

The study offers four contributions. First, the study analyzes the negative disclosure effect. As pre-registered, disclosing the information that an AI application was used to identify job candidates leads to significantly less interest in a job offer among them. Second, the study contributes to conceptual understanding and explores empirical insights on how advances in AI applications can improve the efficiency in data-intensive managerial tasks, such as searching and screening candidate profiles. The exploratory results indicate a positive deployment effect as the person–job fit determined by the leaders is positively correlated with the assessment of the AI application. Still, deploying AI does not come without risks and challenges to public sector decision-making (Zuiderwijk et al., 2021), so the study results point to future research designs that assess these effects, for example with regard to biases and potentially discriminatory outcomes. Third, in a realistic and natural setting, it addresses benefits as well as pitfalls inherent in using AI applications (Tong et al., 2021) in order to facilitate evaluations of AI applications in the public sector. Fourth, this study offers a conceptual step toward understanding digital, employer-driven recruitment. Such data-driven, innovative approaches to address current public sector challenges like recruitment offer rich opportunities for future research to bridge AI application studies with contextual research.

2 THEORY AND HYPOTHESES

Employer-Driven Recruitment Enabled by AI Applications

Several public administration studies have asked the question of how to attract motivated and qualified talents to work for the government (for a review, see Korac et al., 2019). As a key resource of public service provision, the attraction of experts and leaders is key for public organizations and becomes a major determinant of organizational assets and policies. Moreover, public sector recruitment has an additional task that might be less relevant for private sector hiring—representing society in the public workforce. Representative bureaucracy is considered to be one way to increase perceived legitimacy of public organizations (Riccucci et al., 2014).

Even though recruitment has become an urgent topic of strategic relevance for organizations (Linos, 2018), recruitment research focuses almost exclusively on the perspective of recruit-driven labor market searches—that is, the individual looks for job openings and applies. Public administration scholars have not yet researched recruiting efforts that work the other way around: employer-driven recruitment. According to representative survey data, about 18% of US employees are hired into their current job via employer-driven candidate search and acquisition (Black et al., 2020). Such direct sourcing capabilities enable an organization to hunt for candidates, often via searches, and contact candidates directly or via intermediaries (such as recruiting firms). In addition to traditional job advertisements, this might help public organizations reach out to candidates with specific skills, values, and motivations (Tavares et al., 2021). It might also help to foster diversity and representation among public employers, who might otherwise fail to represent society and could face prejudices among certain target groups of recruits on the labor market (Cordes & Vogel, 2022).

As employer-driven recruitment is especially data-intensive, digitalization and tools such as AI applications can boost such practices of organizational candidate hunts (Black et al., 2020). In general, AI applications can be applied in many different ways to support hiring, for example, by predicting vacancies, optimizing job descriptions, targeting job advertisements, parsing and screening CVs, enhancing selection processes (e.g., support testing and screening, background checking, and automated scheduling), monitoring employer branding, and engaging with candidates (e.g., chatbots) (Albert, 2019). AI applications can make it easier and cheaper for employers to strategically search for candidates.

Employer-driven recruitment facilitated by AI applications has the potential to fundamentally change recruitment for three reasons in particular. First, it allows employers to tap into the passive labor market—the large group of employees of other organizations that are dissatisfied and have turnover intentions, but who are not already actively looking for job advertisements of other employers. Second, it can enable more strategic recruitment (Elfenbein & Sterling, 2018): By being able to analyze the big data of candidates' social media job profiles efficiently with support of AI applications and pre-select specific competencies, employers can develop approaches to hire candidates that can contribute to the future development and learning of the organization, rather than just hiring them as replacements for predecessors. Third, employer-driven recruitment might help to compensate for weaker employer branding since many public organizations might not be able to invest large budgets in employer branding campaigns like private competitors. An employer-driven approach allows public employers to increase their candidate pool by contacting candidates that might not otherwise take notice of their job offers, in addition to the conventional approach of posting job advertisements and waiting for applications.

Signaling Theory

To understand how individuals react to employer-driven recruitment, this study uses signaling theory (Connelly et al., 2011). Signaling theory helps to understand how candidates infer from messages they receive from public organizations. Signals play a key role when candidates process their environment as they have little information about employers due to information overload in the noisy labor market (Ehrhart & Ziegert, 2005). Candidates often apply heuristics to cope with this situation of information asymmetry and high uncertainty (Šverko et al., 2008). They rely on signals that are conveyed from any information they have and from which they infer the employer value propositions of an organization.

Applied to individuals receiving direct sourcing messages from public organizations, the signaling mechanism predicts that these individuals use the limited information available—here, from the direct sourcing message they receive—as signals of what it might be like to work for this public employer. When individuals receive a direct sourcing message that signals interest in hiring them, these messages provide signals that affect the interest in a job. Sending convincing signals during the earliest stage of recruiting is important because if candidates are not initially convinced, they might not give further attention to the employer (Keppeler & Papenfuß, 2022a). Sending a direct sourcing message with a job offer should send a signal of appreciation to the recipients. This message could serve as a signal that raises self-esteem and, thus, increases interest in the offer as candidates are actively addressed and searched for in a job market context where they are accustomed to having to act themselves.

Disclosure Effects: Bridging Signaling Theory and Algorithm Aversion

Disclosing the use of AI applications is often legally and ethically required to ensure accountability (Franzke et al., 2021). Previous research recommends being transparent in terms of AI application algorithms and to use transparent, interpretable models, especially in the public sector (Busuioc, 2021). Some research argues that disclosing the use of an AI application might function as a signal that generates interest. Digital recruitment tools can lead to the perception that an organization is more attractive, signaling an "innovative, open, and leading-edge" employer (van Esch et al., 2021, p. 120). Some candidates might even prefer algorithmic rather than human evaluation of their CV (Fumagalli et al., 2022). However, the findings on the impact of AI applications on organizational attractiveness are mixed (Langer & Landers, 2021).

According to research on algorithm aversion (Dietvorst et al., 2015), informing about the use of an AI application may lead to a negative perception of the results of the process. In other words, individuals react with aversion once the use of AI applications is disclosed, relative to non-disclosure. Algorithm aversion describes that “although evidence-based algorithms consistently outperform human forecasters, people often fail to use them after learning that they are imperfect” (Dietvorst et al., 2018, p. 1155). While people appreciate algorithmic decision-making in certain situations, such as in visual estimation tasks or predicting song popularity (Logg et al., 2019), algorithm aversion research shows that, on average, people appear to be unwilling to use algorithms in domains where they face inherent uncertainty, for example, medical decision-making (Longoni et al., 2019). The objection of algorithms cannot only be observed for active users, such as decision-makers (Dietvorst et al., 2015; Maasland & Weißmüller, 2022), but also for consumers or passive users. People especially object to algorithms in decision-making processes that may involve morally relevant trade-offs (Dietvorst & Bartels, 2021), even when they recognize that the AI applications’ decisions may be objectively fairer or outperform human decisions (Tong et al., 2021). This is also true for situations where consumers fear that their subjective preferences or their unique situation do not align with the maximization strategies of algorithms (Castelo et al., 2019; Leung et al., 2018).

This study argues that negative perceptions of disclosing the use of AI applications can be applied to the recruitment context. Hiring is associated with uncertainty, subjective preferences, self-expression, and a qualitative evaluation of unique CVs. Trust and procedural fairness are key. Therefore, candidates might prefer human judgment per se. Research indicates that people prefer human decision-making in uncertain domains with high importance of moral, trustworthy, and fair decisions and the opportunity to evaluate unique characteristics accordingly (Dietvorst & Bharti, 2020). People are more likely to attribute all these characteristics to humans than to AI applications. This study hypothesizes as follows:

H1: Signaling a person–job fit determined by a recruiter in a direct sourcing message increases the interest in a job with a public employer.

In contrast, people see AI applications as inescapably associated with reductionism (Newman et al., 2020). Candidates will likely resist the notion that algorithms are capable of accounting fairly for qualitative human attributes and may not feel sufficiently valued in a situation that is associated with moral aspects (Dietvorst & Bartels, 2021). Candidates are more likely to show a negative disclosure effect when receiving a signal in a direct sourcing message in which an AI application determined their fit for receiving this job offer. The following is hypothesized:

H2: Signaling a person–job fit determined by an AI application in a direct sourcing message decreases the interest in a job with a public employer.

People do not generally oppose algorithms per se—they even appreciate their use for certain forecast tasks with quantifiable standards (Logg et al., 2019). Algorithm aversion might be mitigated by signaling augmentation instead of automation (Burton et al., 2020). If organizations combine AI applications with human decision-making to create a pair, this could be perceived as the most effective and fairest option (Newman et al., 2020). Candidates might accept the signal that a recruiter makes a moral decision and weighs all unique criteria with due diligence and qualitative evaluation based on the pre-work of an AI application. This study hypothesizes as follows:

H3: Signaling a person–job fit determined by both a recruiter and an AI application in a direct sourcing message increases the interest in a job with a public employer.

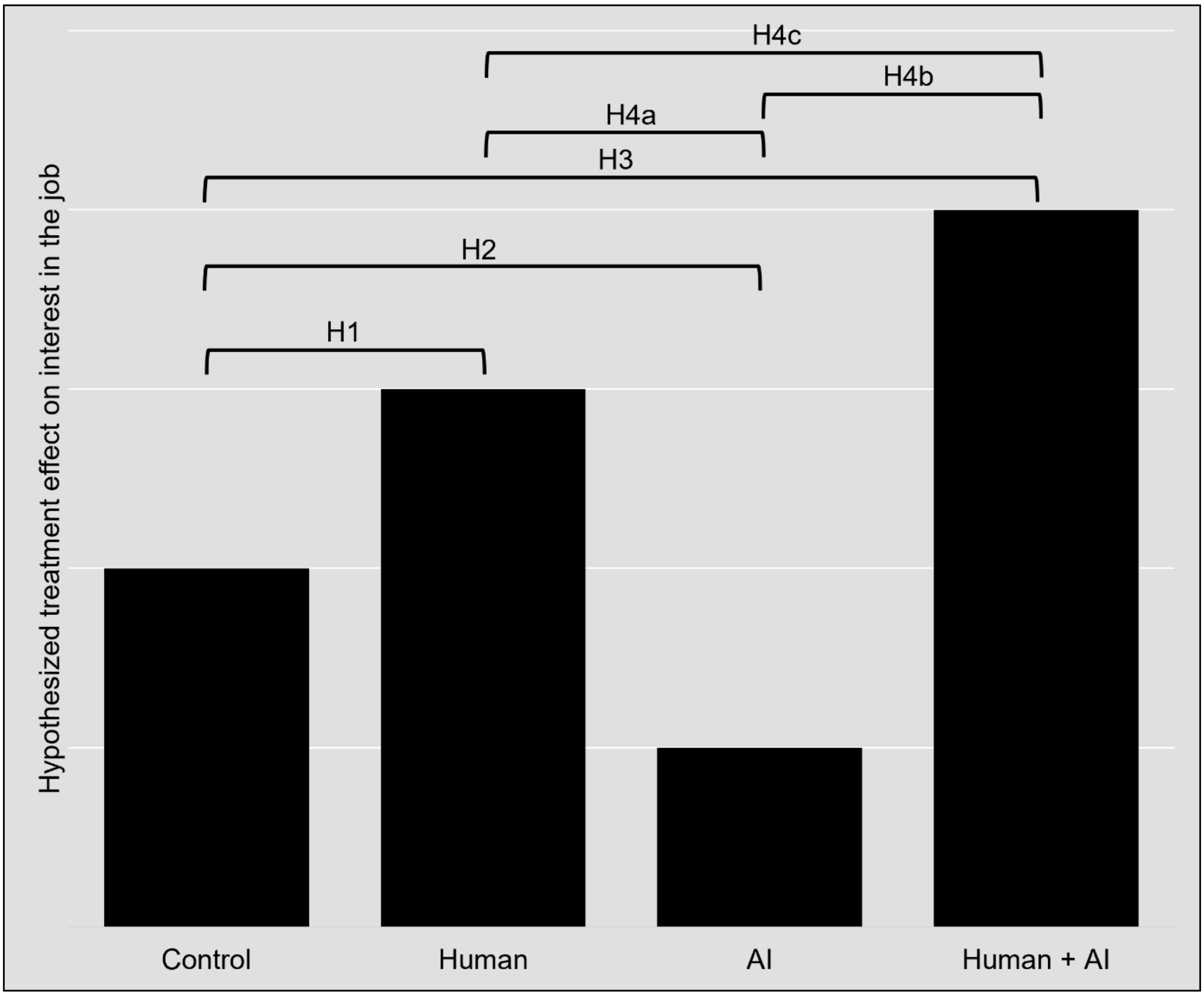
Finally, to compare the three experimental conditions (AI application, recruiter, or combination signaled) with each other, the study hypothesizes as follows (see Figure 1 for an overview):

H4a: Signaling a person–job fit determined by an AI application leads to lower interest in a job with a public employer compared to when signaling a person–job fit determined by a recruiter.

H4b: Signaling a person–job fit determined by an AI application leads to lower interest in a job with a public employer compared to emphasizing a person–job fit determined by both a recruiter and an AI application.

H4c: Signaling a person–job fit determined by a recruiter leads to lower interest in a job with a public employer compared to emphasizing a person–job fit determined by both a recruiter and an AI application.

Figure 1: Hypothesized Treatment Effects On Interest In A Job (2x2 Factorial Design)



Disclosure and Self-Processing: The Role of Social Identity and Risk Aversion

Candidates not only process their environment but also their self in the context of job market signaling (Ehrhart & Ziegert, 2005). According to social identity theory, individuals' social identities interact with the inferences they make from organizational signals (Highhouse et al., 2007). As gender plays a key role in the concept of self and behavior, it can influence reaction to job choices (Kjeldsen & Jacobsen, 2013) and signaled organizational characteristics (Keppeler & Papenfuß, 2021). This study presumes that because of different social identities, women and men react differently to a signal from an AI application in a message. Specifically, women are less likely to be attracted to an AI application signal as their social identity could be related to lower technology acceptance (Ochmann & Laumer, 2020). Women might show a lower acceptance of AI applications as they are, on average, more risk averse (Friedl et al., 2020) and may apply a more skeptical and rational mindset (Hügelschäfer & Achtziger, 2014) to such AI applications. The following is hypothesized:

H5: Female individuals are less likely to have an interest in a job with a public employer if a direct sourcing message signals a person–job fit determined by an AI application.

Lower technology acceptance because of higher risk aversion might also apply to public employees. There is an ongoing discussion in the literature about whether public employees are more risk averse (Tepe & Prokop, 2018). Studies indicate a link between public sector affiliation and biased risk behavior (Weißmüller, 2021). Because of differences in risk aversion, individuals who are currently working in the public sector react differently to the disclosure of the use of an AI application in a direct sourcing message. Specifically, public employees are less likely to be attracted to an AI application signal as their aversion to risks might relate to a lower technology acceptance:

H6: Individuals employed in the public sector are less likely to have an interest in a job with a public employer if a direct sourcing message signals a person–job fit determined by an AI application.

Deployment Effect: AI Applications and Leaders Determining Person–job Fit

Deploying AI applications implies potential efficiency gains, such as relieving public employees from mass transactional duties by automating data-intensive tasks and facilitating informed decision-making (Zuiderwijk et al., 2021). Public organizations increasingly consider adopting AI applications to automate data-intensive, time-consuming tasks, to increase scalability, decrease costs, and improve quality (Young et al., 2019). This can result in fundamental changes to decision-making (Ranerup & Henriksen, 2022).

The use of AI applications might make the decision-making more efficient for two reasons. First, AI applications can quickly analyze structured data. In the present context of employer-driven recruitment, the AI application can relieve public employees from the mass transactional task of searching and filtering millions of profiles on social media job platforms. These massive databases of regularly updated candidate profiles enable direct sourcing of candidates and can reduce the cost of finding employees (Black et al., 2020). An AI application might outperform human search endeavors in terms of efficiency. Second, AI applications can generate more accurate results for the analysis of large and complicated datasets by drawing on training datasets that exceed human memory (Tong et al., 2021). AI applications can analyze large volumes of applicant profiles over time to determine assessments such as fit between person and job.

However, research points to challenges of deploying AI applications in the public sector at different layers (Wirtz & Müller, 2019; Zuiderwijk et al., 2021). On the policy layer, there are ethical challenges, legal as well as political issues, and societal discussion points regarding legitimacy, social acceptance, and trust (Glikson & Woolley, 2020). On the layer of application of AI, there are organizational and managerial challenges, as well as questions with regard to the lack of specific skills in the public sector (Neumann et al., 2022). At the layer of functions and technology infrastructure, challenges related to data and interpretation exist. Public sector decisions—evaluating the person–job fit of a candidate in this case—often require individual judgment. It can be difficult to translate all relevant specific aspects into algorithms as may be required by case-by-case decisions (Binns, 2022).

Public administration research especially points towards fundamental changes to decision-making (Bullock, 2019). Digital discretion— that is the "use of computerized routines and analyses to influence or replace human judgment" (Busch & Henriksen, 2018, p. 4)—can change organizational outcomes and values (Bullock et al., 2020). This study explores this empirically in the context of a natural decision-support arrangement, in which an AI application might inform and augment decision-making, but where a human finally decides (Selten et al., 2023). Specifically, the study analyzes the extent to which the deployment of AI in determining the person–job fit of candidates can predict the person–job fit determined by a leader. It might already be an efficiency gain for leaders if the person–job fit determined by an AI application is only to a small extent positively related to their human perception. This is due to two reasons. First, while decisions in recruitment are among the most important organizational decisions (Guion, 2011), they are also difficult and characterized by a complex weighing of candidates' strengths and weaknesses. This gives an elevated level of discretion to decision-makers and makes it reasonable to assume rather low associations for different person–job fit assessments. For example, trained recruiters can come to quite different results even if they attend the same job interviews (Sackett et al., 2021). Second, employer-driven recruitment can include the screening of millions of candidate profiles. Relieving recruiters from such data-intensive search processes with an AI application can contribute to an efficient evaluation of candidate profiles. Human recruiters can allocate their attention to screening profiles that are relevant rather than sorting out numerous irrelevant profiles. This leads to the following exploratory, not pre-registered hypothesis:

H7: The person–job fit determined by an AI application is positively associated with the person–job fit independently determined by a leader.

3 FIELD-EXPERIMENTAL SETTING AND DESIGN

Setting of the Public Employer

Stadtwerke Heidelberg is a public enterprise with around 1,000 employees supplying approximately 200,000 people with public services such as electricity, grid services, gas, water, heating, public transport, parking, and public baths. Because there is full employment and strong private sector competition paying high wages on the regional labor market, this public organization faces notorious challenges in recruiting. Their conventional way of hiring—that is, posting job openings in newspapers and online or relying on other employees' referrals—often does not attract enough qualified individuals for expert and leading positions.

Public enterprises offer a useful case for studying public sector recruitment and the role of AI applications for five reasons. First, there is an increasing demand in the literature to consider public enterprises as research objects (Andrews et al., 2022) because a significant share of public services worldwide are provided by public enterprises, and they contribute to the understanding of publicness and the role of ownership, funding, and control (Bozeman & Moulton, 2011; Bruton et al., 2015). This empirical context can help to research the boundary conditions of theories developed in public administrations or extend them. Second, public enterprises are owned by public actors; in the present case, the city of Heidelberg owns 100%. Third, they are often funded by the taxpayers as their market-based activities are often enough to finance non-profit tasks or infrastructure investments. Fourth, public enterprises are under political control that can be comparable to public administrations. Specifically, politicians control the appointment of executive directors and strategic HR policies (Keppeler & Papenfuß, 2022b; Papenfuß & Schmidt, 2022). Fifth, and finally, like public administrations, public enterprises are often in the same way in direct interaction with citizens, mostly operate under the same collective labor market agreements, and repeatedly recruit from the same market segments.

This trial was co-designed with the public employer to evaluate the use of an AI-based application tool for employer-driven recruitment in 2021. The co-design process involved iterative collaboration with HR experts from the public employer and the umbrella organization of public enterprises. Including their different types of expertise and resources helped to design the research question, the treatment design, the search strategy for candidates, and the overall implementation of the trial in a real recruitment process to create relevant knowledge (Jensen et al., 2022; Schwoerer et al., 2022). The public organization considered creating its own direct sourcing capabilities so that it could hunt for candidates itself. As the human resource managers in the public organizations have very limited resources, an AI application is tested for direct sourcing.

The AI application is enabled by machine-learning techniques in the area of natural language processing and recommendation systems, drawing on big data analysis of the substantial number of candidate profiles on social media job platforms. The tool can relieve from the tedious, tough, and time-consuming online search for potentially relevant candidates on social media job platforms such as LinkedIn or Xing (a German-speaking equivalent). It comprises four key components. First, it enables recruiters to search through diverse social media job platforms based on job title, competencies and skills, or similarity to specific candidates. The AI application can find individuals with the necessary skills or comparable tasks but with a different job title. Second, it recommends skills or tasks that are likely to be relevant for the specific job opening based on what the recruiter already inserted. Third, drawing on multiple sources, such as profiles of the same candidates on different platforms, the AI application builds a single profile and recommends the contact options with a high probability of a response. Fourth, it calculates three scores (0–100%): person–job fit, openness to move, and openness to job change. To evaluate this, the AI application draws on profile data on competencies, skills, and social media behavior. According to the company website, this AI application has been on the market for several years and is used by more than 500 customers.

Design and Procedure of the Field Experiment

The study design can be described as a “natural field experiment” (Harrison & List, 2004, p. 1033)—that is, the random treatment assignment is implemented in a natural environment—which in this case is a recruitment process for three real jobs. The experimental procedure followed five steps. First, three job openings were chosen in the public organization. Previous job postings were not successful. For these three positions, 2,000 candidates (600 financial application experts, 1,000 utility application experts, and 400 tech team leaders) were identified through the AI application. All these individuals showed a basic fit for one of the specific jobs in the public organization. The recruiters double-checked the preselection of the AI application; they replaced candidates that were retirees or had worked for the public employer previously. The AI application offered the following data on the candidates: gender (1=female, 0=male), current job in the public sector (1=yes, 0=no, 99=residual), distance from the current place of residence to the public organization (in km), and duration of the current employment (in months).

Second, the 2,000 candidates were randomized on the individual level. Randomization was stratified by gender as well as current affiliation to the public sector and performed using the software Stata with a reproducible seed.

Third, the individuals were randomly assigned to a female or male recruiter and to one of the four experimental groups. The two recruiters sent the direct recruiting messages from their professional accounts on the social media platform “Xing”. As the platform limits the number of sent messages per day, the sending procedure began on October 27 and ended on November 22, 2021. The field experiment follows a 2x2 factorial design, with the two disclosure dimensions signaling to candidates that their person–job fit was determined by recruiters or an AI application. All direct sourcing messages were personalized (candidate’s name and place of residence, highlighted in bold) and the recruiter’s signature. The control message text illustrates this:

“[Subject]: You are convincing, **Ms. Smith**!

> Dear Ms. Smith,
> In our search for a new team member, we came across you because you are well versed in **job title 1/2/3**. Looking at your profile, we believe that you may be an excellent fit for us.
> Please feel free to reply to our message if you are also interested in further personal contact.
> We at Stadtwerke Heidelberg really offer meaningful jobs. With us, work and private life are in balance. Our team goes home in the evening with a good feeling.
> Best regards to **[residence of candidate]**!
> Andrea/Michael [full name of female/male recruiter – randomized]
> Personnel Management
> Stadtwerke Heidelberg”

Each message is shown in Figure A1 with a translation in Table A1. The messages for the three treatment groups were identical, but the subject lines and a second paragraph varied:

> Treatment Human: “You are convincing our team, Ms. Smith! […] This has been identified by our recruitment team. Our recruitment team has searched profiles on Xing and identified that you could be a valuable team member.”
>
> Treatment AI: “You are convincing our AI, Ms. Smith! […] This has been identified by our recruitment software, which is based on artificial intelligence. Our recruitment AI searched profiles on Xing and identified that you could be a valuable team member.”

> Treatment Human + AI: "You are convincing us and our AI, Ms. Smith! […] This has been identified by our recruitment team with our recruiting software, which is based on artificial intelligence. With the support of AI, our recruitment team has searched profiles on Xing and identified that you could be a valuable team member."

Fourth, to test the disclosure effect, data was collected on whether candidates responded to the message (1=yes, 0=no) and whether they showed interest in the job in the public organization (1=yes, 0=no). A second message with an individualized link was sent to the candidates who showed interest. The link led them to the online application system of the public employer so that link click data could also be gathered—the number of clicks and a binary variable click to measure whether someone clicked at least once (1=yes, 0=no).

Fifth, to explore the deployment effect, the study took data from the AI application and generated a list for each of the three jobs. For each job, a subsample of 250 candidates was randomly drawn. Then, the three department heads received the list of the randomly drawn candidates in order to rate their person–job fit on a scale of 0 to 100%. These three leaders had the opportunity to assess the same data as the AI application (listed data, the full candidate profile on the social media job platform, and additional online search). The leaders were not restricted in data access or time. They were only blinded regarding the three scores of the AI application—that is, they did not receive information on how the AI application determined the person–job fit, openness to move, and openness to change the job.

The study was approved by the ethical committee of Zeppelin University on September 22, 2021, before it was conducted. It followed established ethical guidelines for randomized control trials in terms of respect for persons, beneficence, and justice. The cooperating public employer contacted users on the social media job platform Xing who had agreed to be contacted with job offers. The employer only contacted individuals with a basic job fit and offered them real job offers. One individual was hired as a result of this study. While all participants received the same accurate information on the job advertised, they were not fully informed about how they were allocated to treatment groups to test their algorithm aversion. This withholding of information was justified because there was no other way to examine their aversion in this setting and little risk of harm (Glennerster & Powers, 2016). This study follows the perception that "withholding information about research hypotheses, the range of experimental manipulations, or the like ought not to count as deception" (Hertwig & Ortmann, 2008, p. 62), but it also acknowledges that different perspectives exist regarding the term deception (Krawczyk, 2019). To embrace these different perceptions of the understanding of deception, the experimental procedure, as approved by the ethical committee, contains a debriefing in the form of a public posting. The cooperation partner posted a press release about the study.

Data and Randomization Check

As shown in Table 1, on average, 26.9% of the candidates are female, 28.6% are currently working in the public sector, the mean distance from their current place of residency to the public organization is about 198 km, and their current employment runs for 57 months on average. As outlined, 50% of them were assigned to the female recruiter. The mean person–job fit of the subsample determined by the leaders is 35.0%. The AI application determined their mean person–job fit with 42.2%, their openness to move with 17.1%, and their openness for a job change with 44.9%. The absolute difference between the person–job fit determined by the leader and the AI application is 27.3%. Figures A2, A3, and A4 additionally illustrate the descriptive statistics for the three variables' person–job fit determined by the leaders and by the AI and the difference between both. Table A2 presents the results of randomization checks.

Table 1: Summary Statistics

Variable	Obs.	Mean	S.D.	Median	Min.	Max.
Female	2,000	0.269	0.444	0	0	1
Public sector	1,954	0.286	0.452	0	0	1
Distance (in km)	2,000	197.917	98.230	230	0	400
Employment duration (in month)	1,836	57.407	57.623	39	1	482
Female recruiter	2,000	0.500	0.500	0.5	0	1
Person–job fit determined by leader	695	35.042	32.019	25	0	100
Person–job fit determined by AI	2,000	42.185	20.608	37	0	95
Openness to move determined by AI	2,000	17.073	5.832	15	1	61
Openness to job change determined by AI	2,000	44.938	10.511	45	5	65
Difference between the person–job fit determined by leader and AI	695	27.345	17.692	29	0	87

4 RESULTS

Analyzing the Disclosure Effects

Of the 2,000 candidates who received a direct sourcing message, 20.8% (415) responded. Of those 415 respondents, 32.3% (134) show interest in the job and 27.7% (115) at least click on the link to the online application system provided in the second message to respondents showing interest. The analysis focuses on interest in the job as the key outcome. Table A3 reports descriptive statistics for all key variables per experimental group. A one-way analysis of variance (ANOVA, Bonferroni-corrected)—$F(3,411) = 4.550$, $p = .0038$, $\eta^2 = 0.032$—reveals significant differences between the experimental groups. Linear regression analysis is applied to estimate the causal effects of treatments on binary outcomes (Gomila, 2021). The results are presented in Table 2.

Table 2: Linear Regression Analysis—Impact of Each Treatment on Interest in the Job

Variables	1	2	3	4
Human	-.148 (.027) .664	-.129 (.285) .068	-.065 (> .999) .078	-.076 (> .999) .084
AI	-.225 (.000) .064	-.182 (.035) .064	-.099 (.890) .073	-.169 (.310) .078
Human + AI	-.166 (.022) .065	-.136 (.270) .067	-.062 (> .999) .077	-.093 (> .999) .084
Female		-.067 (.561) .051	.229 (.399) .120	-.069 (> .999) .051
Public sector		.091 (.285) .048	.088 (.414) .048	.160 (.954) .099
Distance		-.001 (.000) .000	-.001 (.011) .000	-.001 (.000) .000
Employment duration		.000 (> .999) .000	.000 (> .999) .000	.000 (> .999) .000
Female recruiter		-.020 (> .999) .046	-.020 (> .999) .045	-.019 (> .999) .046
Female x Human			-.332 (.248) .153	
Female x AI			-.424 (.030) .143	
Female x Human + AI			-.376 (.144) .155	
Public sector x Human				-.143 (> .999) .140
Public sector x AI				-.029 (> .999) .135
Public sector x Human + AI				-.113 (> .999) .141
Constant	.455 (.000) .048	.599 (.000) .073	.526 (.000) .078	.576 (.000) .079
Observations	415	390	390	390
R-squared	0.032	0.080	0.101	0.084

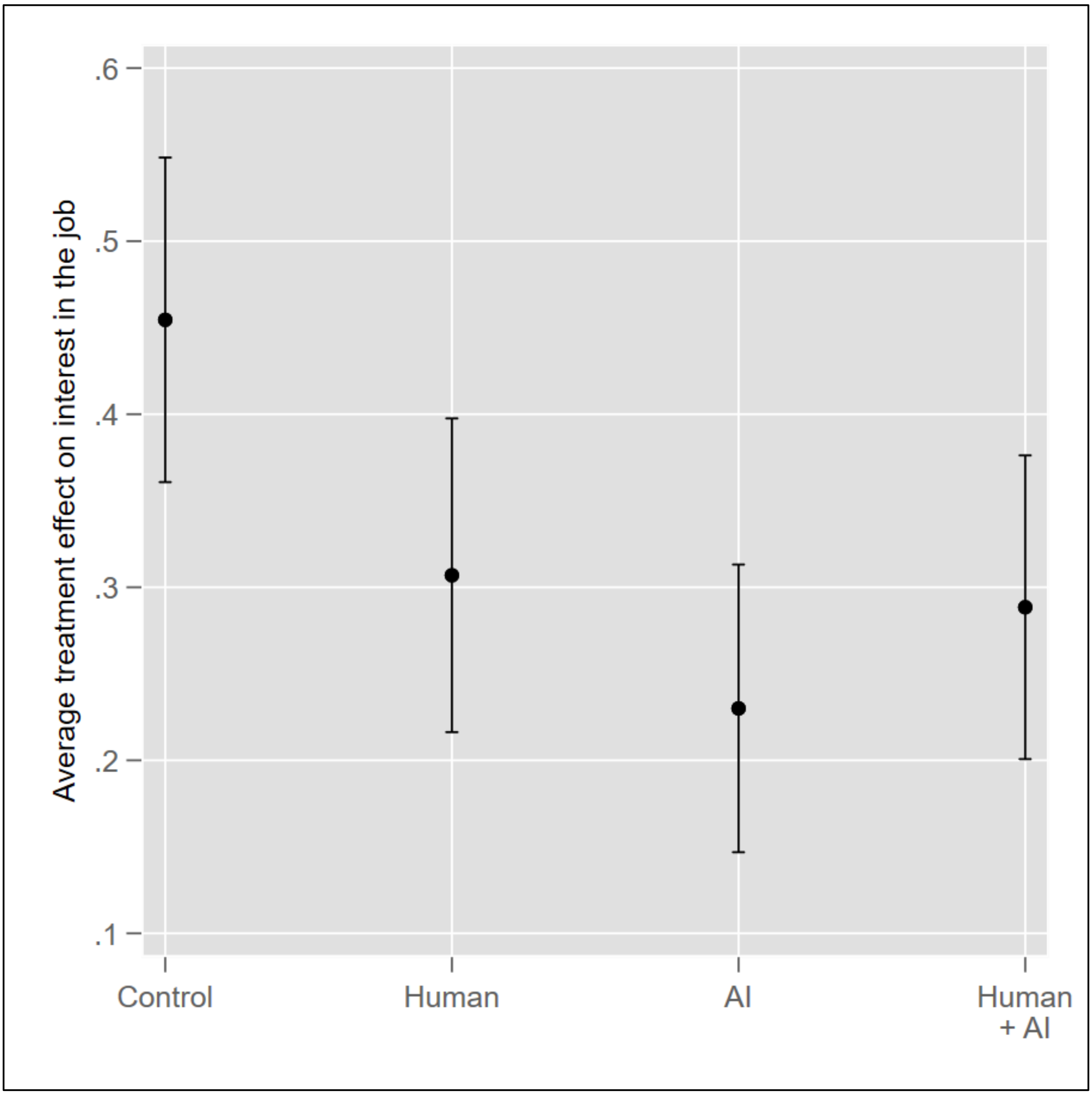
Note: This table shows the impact of the treatment on showing interest in the job in the public organization offered in a direct sourcing message. The regressions in columns 3 and 4 test the interaction between treatment arms and gender and current affiliation to the public sector, respectively. Beta-coefficients are displayed, followed by p-values (in parentheses, Holm-Bonferroni corrected) and robust standard errors.

Models 1 and 2 present the impact of the signals in the direct sourcing messages, without and with controls. In contrast to H1, there seems to be suggestive evidence that signaling a person–job fit determined by a recruiter seems to be significantly less effective than just sending a shorter message that remains silent on that matter, as in the control group. In line with H2, the AI message leads to a significant reduction of the interest in the job in both models. H3 does not find empirical support; mentioning both human and AI does not lead to increased interest in the job. In turn, there seems to be suggestive evidence that it leads to less job interest than the control group. The distance between a candidate's place of residence and the public organization significantly decreases the job interest, but the effect size is small.

Figure 2 visualizes the treatment effects. Although the significant negative effect of the disclosure of AI in direct sourcing messages can be found (β= -.182, p= .035, SE= .064), contrary to the expectations stated in H4a, H4b, and H4c, no significant differences in the comparison of treatments can be detected.

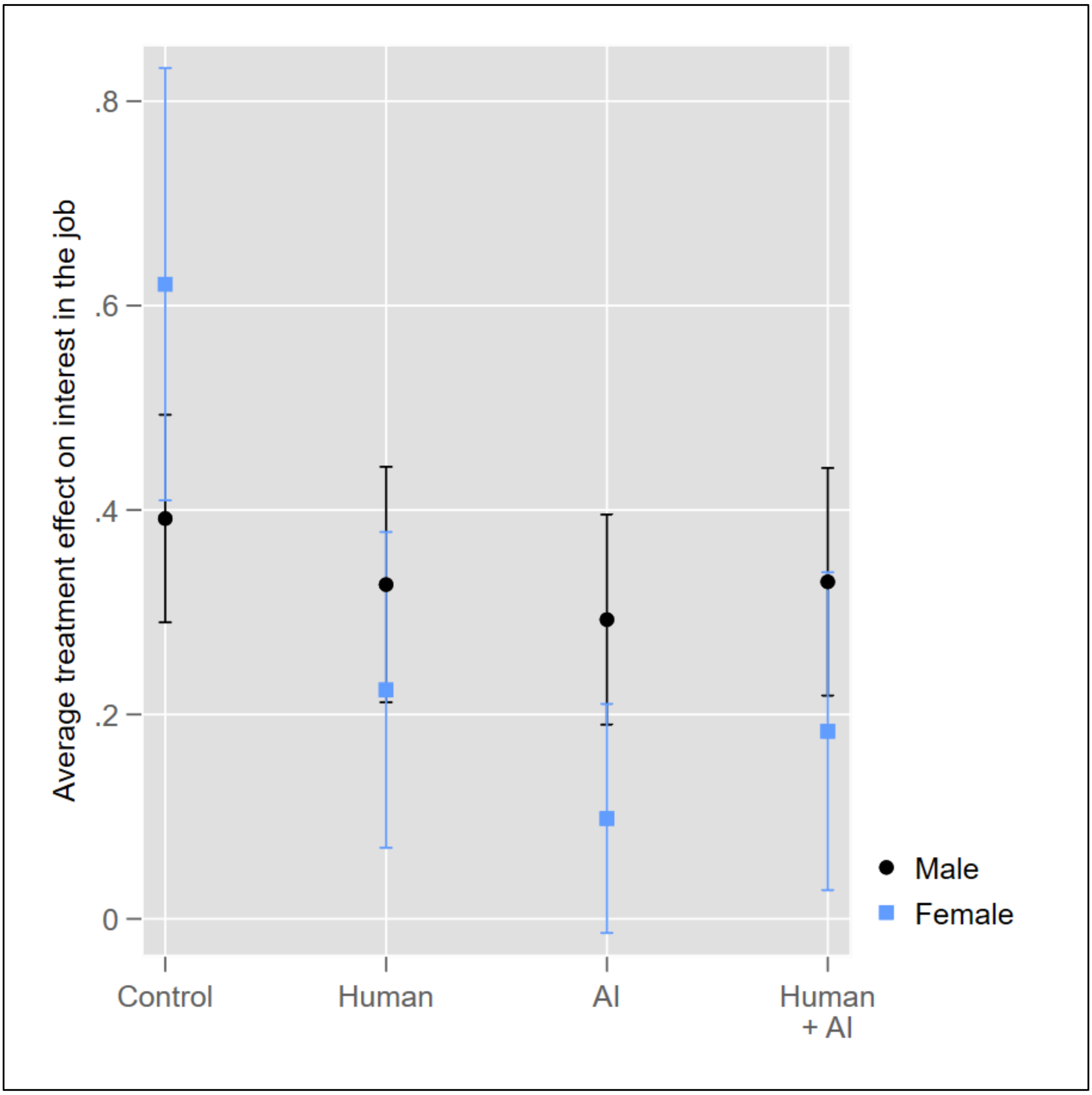
Model 3 in Table 2 considers the interaction of gender with the treatments. In line with H5, women are significantly less likely to show interest in a job when it is disclosed that the AI determined the person–job fit. This result (β= -.424, p= .030, SE= .143), visualized in Figure 3, indicates that the negative disclosure effect is driven by female candidates. In turn, model 4 does not support H6. Candidates' current employment in the public sector does not moderate the effect of disclosure on job interest.

Figure 2: Marginal Means Plot—Effects of the Experimental Groups on Interest in the Job



Note: Points represent marginal means, vertical bars 95% confidence intervals.

Figure 3: Marginal Means Plot—Interaction Effect of the Experimental Groups and Gender on Interest in the Job



Note: Points represent marginal means, vertical bars 95% confidence intervals.

Exploring the Deployment Effect

The study uses the person–job fit determined by the leader as a dependent variable to explore the deployment effect. The matrix in Table A4 shows a significant, positive correlation between the person–job fit determined by the AI application and the leader (r=.323, p < .001).

Table 3 responds to the exploratory hypothesis H7. Model 1 and 2 (with control variables) show that the AI application's person–job fit score is significantly and positively associated with the independently determined person–job fit score of the leaders. The AI application appears to be able to predict, to some extent, how human department leaders will determine the person–job fit of candidates. For each percentage point increase in the person–job fit determined by the AI, the person–job fit determined by the leader increases by an estimated 0.47 percentage points. This result is visualized in Figure 4 and supports H7.

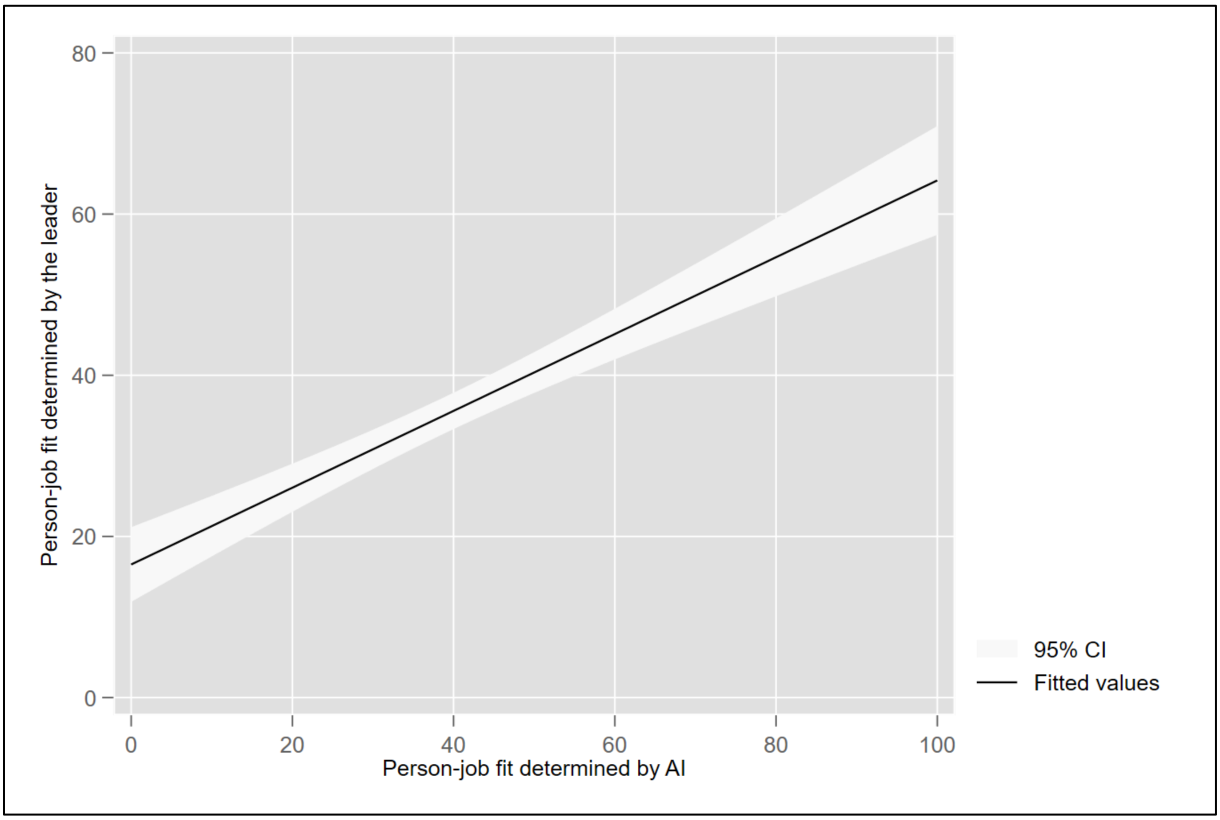
Table 3: Linear Regression Analysis of the Person–job Fit Determined by the Leader

Variables	1	2
Person–job fit determined by AI	.477 (.000) .052	.470 (.000) .054
Openness to move determined by AI		-.122 (.575) .217
Openness to job change determined by AI		.135 (.248) .117
Female		-5.605 (.051) 2.870
Public sector		5.136 (.061) 2.734
Distance		-.038 (.003) .013
Employment duration		-.015 (.523) .024
Constant	16.512 (.000) 2.239	21.432 (.012) 8.494
Observations	695	636
R-squared	0.104	0.122

Note: This table shows the relationship between the person–job fit determined by the AI application and the leaders. Beta-coefficients are displayed, followed by p-values (in parentheses) and robust standard errors.

As a different leader determined the person–job fit for each job, Table A5 presents the results for the three job-specific subsamples. In all models, the person–job fit determined by the AI remains a significant predictor variable. In addition to that, Table A5 and A6 explore what other factors may relate to the person–job fit determined by the AI and the leader. The results indicate that for the position of the tech team leader, there is a significant, negative relationship between female gender and the person–job fit determined by the leader. Further, model 2 shows that female gender is negatively associated with the person–job fit determined by the AI application. These findings might indicate biases that could lead to discrimination.

Figure 4: Two-way Linear Prediction Plot of Person–job Fit Determined by AI Application on the Person–job Fit Determined by Leader



Note: Line represents fitted values, along with the 95% confidence intervals (CI).

Additional Analyses

To assess the robustness of the identified disclosure effects on interest in the job, Table A7 presents the results of linear regression analyses on the response to the direct sourcing message and the clicks on the link to the career page in the second message. Both analyses lead to the same results. Table A8 shows that current employment in the public sector is negatively associated with the openness to move determined by the AI application.

5 DISCUSSION

Disclosing the Use of AI Application of Public Organizations

The results show a negative disclosure effect. Being identified by an AI application significantly reduces interest in the job among candidates. This can be explained by algorithm aversion since decisions in the hiring context can be perceived as related to moral, trustworthiness, fairness, and the evaluation of unique characteristics (Dietvorst & Bartels, 2021). This contributes to the theoretical basis of the human–AI interaction in the public sector, which previously focused on active users of AI applications such as public employees. Passive users, such as job candidates or citizens in general, can show aversion to AI applications in the public sector. This aversion can lead to less interest in or acceptance of decisions, even if they are beneficial, such as job offers. This can undermine the usefulness of AI applications because people can be reluctant to accept and use insights and support of algorithms in certain situations (Tong et al., 2021), even if it is superior to human decision-making (Dietvorst & Bharti, 2020) and reduces bias (Newman et al., 2020).

As the disclosure induces negative perceptions about the use of AI applications, one could question the extent to which transparency is desirable. For example, citizens seem to be willing to trade away transparency over effectiveness gains (König et al., 2022). However, beyond the growing concerns against opaque algorithmization of public sector decision-making (Meijer et al., 2021) and threats to the legitimacy of this approach (Grimmelikhuijsen & Meijer, 2022), not being transparent is neither a likely solution nor is it in line with public sector values such as accountability (Busuioc, 2021) and trust (Grimmelikhuijsen, 2022). Mandatory disclosure policies need to be complemented (Tong et al., 2021), for example, by boosting algorithmic literacy. Furthermore, improvement on the behavioral design and communication of AI applications in decision-making is needed for both active and passive users to understand how it engages with their intuition and incorporates the perspective of a human user (Burton et al., 2020). Human-in-the-loop decision-making in particular is proposed as a way to profit from the performance enhancement of augmented human-algorithm decision systems while also ensuring decision autonomy and the opportunity to inform about, justify, and explain decisions to provide accountability (Busuioc, 2021). According to the results, the augmentation signal (human +AI) leads to a job interest rate that is comparable to the recruiter (human) group.

Furthermore, the results highlight the heterogeneity in the reactions of passive users to the AI signal. The negative disclosure effect is moderated by gender: only 8.33% of female candidates show interest. Differences related to social identity can affect algorithm aversion. This is relevant as female candidates are already often underrepresented among expert or leading positions in public organizations. To ensure representativeness among public employers, it is key to ensure not only discrimination-free selection (Jankowski et al., 2020) but also recruitment activities that attract diverse candidates. Therefore, future research can build on the approach of target group-specific candidate–employer communication (Keppeler & Papenfuß, 2021) to understand how public employers can foster representative bureaucracy and diversity in recruitment. Additionally, future representative bureaucracy research might explore algorithm aversion among other dimensions of diversity in addition to gender. Depending on their social identity and the context, some groups with a lack of representation might favor algorithmic over non-human decision-making (Miller & Keiser, 2021).

Deploying AI Applications in the Public Sector

This exploration of the deployment of an AI application in a public organization shows that the person–job fit determined by an AI is positively associated with the person–job fit determined by leaders. Approx. 10% of the variability in the leaders' assessment is explained (model 1 in Table 3). Reflecting this result in the light of the digital discretion debate, AI applications can change organizational outcomes and values, such as professional, people, ethical, and democratic values (Busch & Henriksen, 2018; Young et al., 2021).

Regarding professional values, the results reveal a perspective through which AI applications can enhance efficiency as a professional value. The AI application could to a certain extent relieve public leaders from screening the person–job fit of candidate profiles. Deploying AI applications could change the reasoning underlying decision-making processes, as assessments could be distributed differently. For candidates with a low person–job fit assessment of the human leaders, the AI application presents an even lower assessment, whereas for candidates with a high person–job fit assessment, the AI application assesses their job-fit even higher. This might be due to the tendency of leaders to assess the person-job fit in line with a “fit/not fit” heuristic (bimodal distribution), while the AI application’s assessment tends to mirror a normal distribution (see Figures A2 and A3). Still, with regard to the high level of discretion, noise, and uncertainty in personnel selection (Sackett et al., 2021), the differences between person–job fit assessments of leaders versus AI applications are smaller than maybe expected (mean 27.3%, SD: 17.7%) and moving away from a binary assessment of person-job fit could lead to more informed decisions.

Regarding people values, there could also be downsides of using AI applications in the context of decisions with a high degree of discretion, such as candidate assessments. For example, if the sole focus is on the person–job fit determined by the AI application, this could lead to a misalignment with organizational values of fairness and diversity. Recruiters might rely on person–job fit determined by AI applications to justify decisions, ignoring other qualitative data that is not readily quantifiable, for example, candidates’ behavior outside the perceptual range of the AI application. Street-level leaders could have less opportunity to co-determine hiring if the use of AI applications centralizes control over hiring on a higher organizational level. This could affect the acceptance of hiring decisions, which form an important basis for subsequent collaboration.

Regarding democratic values such as accountability and representativeness, AI applications can suffer from technical inscrutability. For example, they could mask statistical discrimination (Jilke et al., 2018) in recruitment. According to the results, this might be the case with the finance application experts: For this position, the person–job fit determined by the AI application is negatively associated with female gender. Statistical discrimination could play a role here, as there are, on average, fewer women in finance and IT (see also Lambrecht & Tucker, 2019). However, as in many cases, this cannot be clarified due to opaque algorithms. Beyond this, studies demand codification, regulation, and monitoring of ethical standards for AI applications; the application of transparent algorithms; and more capabilities and competencies among public employees to work with AI applications (Wirtz & Müller, 2019).

Regarding ethical values, the results indicate that AI applications might foster harm discovery and improve fairness. In the specific case of employer-driven recruitment, AI applications can inform recruiters about a candidate with a high person–job fit who might have been perceived as not fitting due to implicit discrimination (Blommaert et al., 2012). In the present data, this may be the case for the tech team leader position, for which the determined person–job fit is negatively related to the female gender. This could be related to implicit biases against women for leading positions (Abraham & Burbano, 2022). Overall, as the use of the AI application might increase the risk of statistical discrimination but reduce implicit discrimination, it will be key to understand the effects of augmented decision-making.

Differentiating Disclosure and Deployment Effects

The study shows the importance of differentiating the effects of AI deployment from AI disclosure and exploring the degree to which potential efficiency gains of the use of AI applications could be offset by their disclosure (Tong et al., 2021). Estimating an overall net effect of using AI applications for employer-driven recruitment in the public sector is difficult and maybe quite inaccurate. What can be stated is that relieving public leaders from data-intensive tasks of filtering millions of candidate profiles with Boolean search by using an AI application may be a rather short-term efficiency gain if the number of interested candidates declines because of algorithm aversion and if representative bureaucracy goals are not met. Therefore, accounting for both deployment and disclosure effects is key to neither over- nor underestimate the true value of AI applications in public administration. The presented field-experimental evidence for a negative disclosure effect offers empirical support for the drawbacks of the use of AI applications in public sector decisions. On the other hand, exploratory analysis of the AI deployment indicates that an AI application can efficiently perform the data-intensive task of identifying and determining the person–job fit of candidates in employer-driven recruitment with results similar to those of a public leader, thus with the potential of relieving them. If public organizations aim at increasing efficacy by implementing AI applications, it will be a key challenge for them to minimize the adverse disclosure effects.

Managerial and Policy Implications

As a first implication for the use of AI applications in public organizations, decision-makers need to be aware of algorithm aversion among both active users (e.g., employees) and passive users (e.g., candidates or citizens). If they use AI applications in contexts where humans perceive to be evaluated (e.g., recruitment or eligibility for public services), it could at least partially reduce aversion against algorithms and increase trust if public managers implement and communicate augmentation—that is, when leaders relate their own knowledge to the information of the AI application for decision-making (Burton et al., 2020).

Second, public managers can learn from this study that the deployment of AI applications can contribute to efficiency gains by reducing search costs in employer-driven recruitment. The AI application allows for the acquisition of information and gives recruiters efficient ways to gather data about the person–job fit of potential candidates. As traditional ways of recruitment become less effective (Black et al., 2020), organizations may invest more in own capabilities for employer-driven recruitment instead of hiring headhunters.

Third, public managers need to take further action to prevent discrimination in recruitment. The present results indicate that both human recruiters and AI applications may not be free from biases that could lead to discrimination, so there is a need for clear accountability, training, and processes that safeguard equal employment opportunities. Hiring decisions are often made under conditions of high uncertainty, constant changes, and sometimes little data (Luan et al., 2019). In this situation, leaders can have a competitive advantage compared to AI applications (Krakowski et al., 2022).

The fourth and final implication is directed to policymakers. With an increasing implementation of AI applications in all sectors, ensuring a power balance is key as AI applications might offer more benefits and power gains to the employer than the employee (Tong et al., 2021). Transparency is often recommended in this context (Busuioc, 2021), but mandatory disclosure of using AI applications can evoke negative reactions, even in beneficial constellations such as job offers. Therefore, transparency should be combined with complimentary policies such as education and public discourse.

Limitations

Although the field-experimental design offers high external validity, it also has limitations. First, the analysis focuses on the specific context of hiring decisions, which may be different from other discretionary decisions. Further, the study analyzes a public enterprise. While more research on public enterprises is important to improving the understanding of the public sector (Andrews et al., 2022; Papenfuß & Keppeler, 2020), they can differ from other organizational forms within the public sector such as public administration units. In the present case, the public might arguably display even more aversion if a public administration—compared to a public enterprise or a private company—uses an AI application for recruitment. Future research on both disclosure and deployment effects could explore the extent to which publicness affects the reactions to and the use of AI applications.

Additionally, the wording of interventions is important. All treatment groups lead to a somewhat lower job interest compared to the control group, which might relate to the fact that all treatments add more words and increase the length of the message. An alternative explanation would be that the candidates find it uncomfortable to read that they were identified in an online search – regardless of whether that search is driven by an AI application or a recruiter. Still, since these effects are no longer statistically significant when control variables (especially gender) are added to the model, the negative AI disclosure effect remains the main robust effect.

While the analysis of the disclosure effects was pre-registered, the hypotheses and analyses on deployment effects are exploratory. The presented results on the association between the person–job fit determined by the AI application with the person–job fit determined by the leaders are just a starting point for future research on the deployment of AI applications in real public sector settings.

Future Research Implications

Employer-driven recruitment promises insights for public administration research. For example, research could explore the extent to which this approach can affect the persistent underrepresentation of certain groups in the public sector (Jankowski et al., 2020). As contacting job candidates might reduce administrative burden and formalization in recruitment, it might help to encourage individuals from minorities to apply for public service jobs (Sievert et al., 2022). Moreover, previous research points to the role of target group differences (Keppeler & Papenfuß, 2021), and consequently, different segments of the labor market might react differently to employer-driven recruitment. While experts and leaders, such as in the present study, can be used to direct sourcing messages by employers and recruiting agencies, frontline employees might react differently.

Regarding the negative disclosure effect, future research can contribute to ongoing scholarly discussions on algorithm aversion about whether it will disappear with increased familiarity with AI applications (Dietvorst & Bartels, 2021). Public services are well suited to assess theoretical questions on how the morality of decisions, the role of the social identity of the users, and the task type affect the reaction to the use of AI applications. Furthermore, qualitatively exploring the text messages that come back as answers to direct sourcing messages may point a way forward. Among the present respondents, clusters of answers can be identified that express happiness (“what an exceptionally great message, great job, compliments”) or curiosity (“a very unusual method, I like that already”), or anthropomorphizing of the AI application (“thank you, dear AI”; “kudos to your AI”). Future research might profit from understanding possible interactions with social identity as especially male respondents seem to anthropomorphize (Ochmann et al., 2020).

The findings on the deployment of the AI application do not imply that AI applications outperform humans in all recruitment tasks. It appears necessary to extend the present analysis to a higher number of AI applications with different algorithms, a higher number of recruiters or leaders that rate the same set of job candidates, and to the actual later performance of hired candidates. Future research is needed to understand the consequences of augmenting the decisions of public leaders with AI applications (Lebovitz et al., 2022) and the complementarity between AI and humans (Krakowski et al., 2022). Overcoming challenges such as algorithm aversion or selective adherence (Alon-Barkat & Busuioc, 2022) is key to realize potential efficiency gains of deploying AI applications and augmenting public sector decision-making.

6 CONCLUSION

Overall, this study disentangles the disclosure and deployment effects of AI applications, contributing to emerging research on how AI applications shape administration and policy in public organizations. The field experiment provides empirical support for both the assets and drawbacks inherent in using AI applications. Understanding the disclosure and deployment effects of AI applications in real public sector decisions is key for future research, policymaking, and practice. On the one hand, using AI applications in practice can evoke aversion among the people that are subject to an algorithmic assessment—in the present case, job candidates. On the other hand, investing in AI applications offers relevant opportunities for public organizations to relieve public leaders from data-intensive tasks. This work aims at spurring future scholarship that takes both sides into account in order to holistically understand the outcomes of AI applications in public-service delivery.

SUPPLEMENTARY APPENDIX

Supplementary material is available at the Journal of Public Administration Research and Theory online.

NOTES

The pre-registration can be found here: doi.org/10.17605/OSF.IO/VHRUP. It contains one further hypothesis that is part of another manuscript.

DATA AVAILABILITY

An anonymized version of the data underlying this article are available in Open Science Framework, at http://www.doi.org/10.17605/OSF.IO/VHRUP. The pre-registration contains one further hypothesis that is part of another manuscript.

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SUPPLEMENTARY ONLINE APPENDIX

Figure A1: Overview of the Treatments (German Original Version; Experimental Groups from Left to Right: Control, Human, AI, Human + AI)

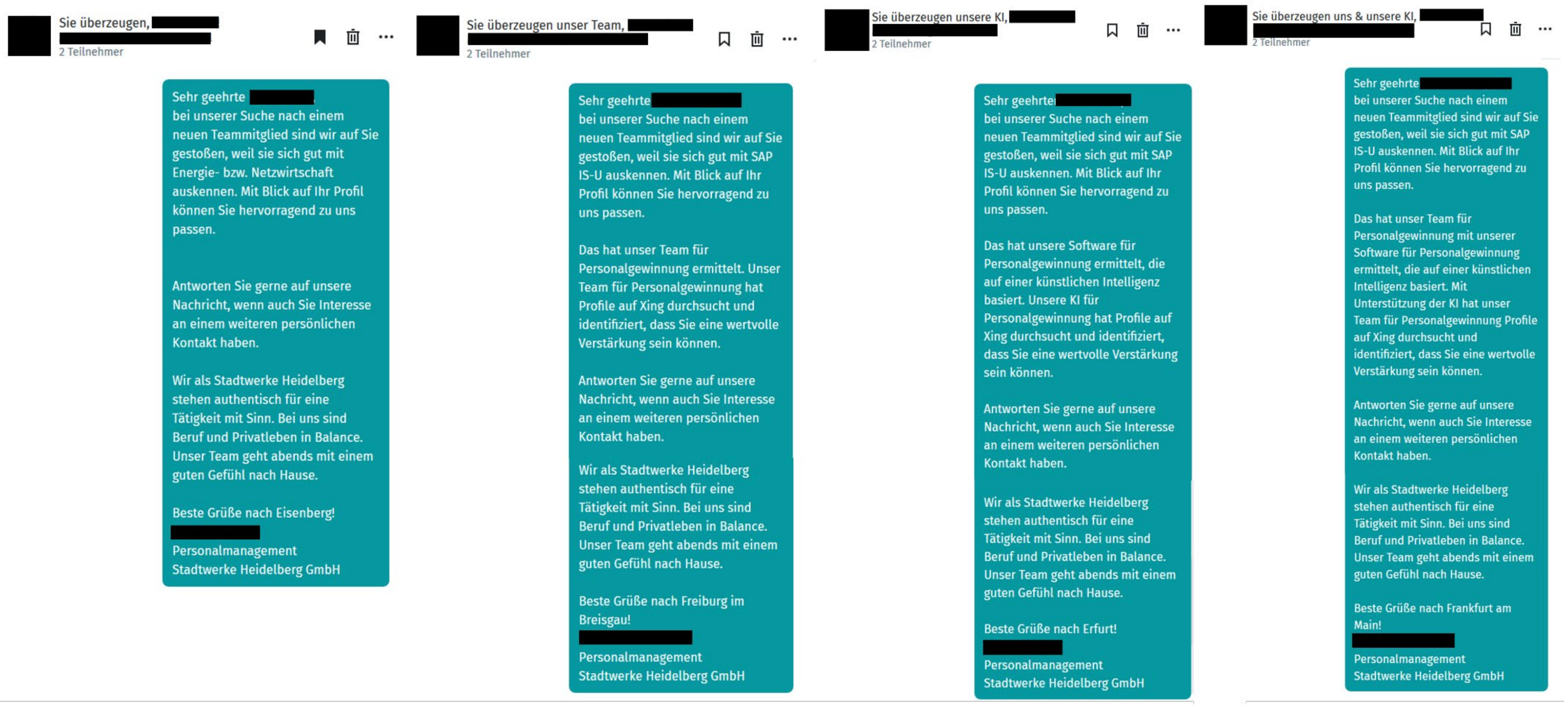
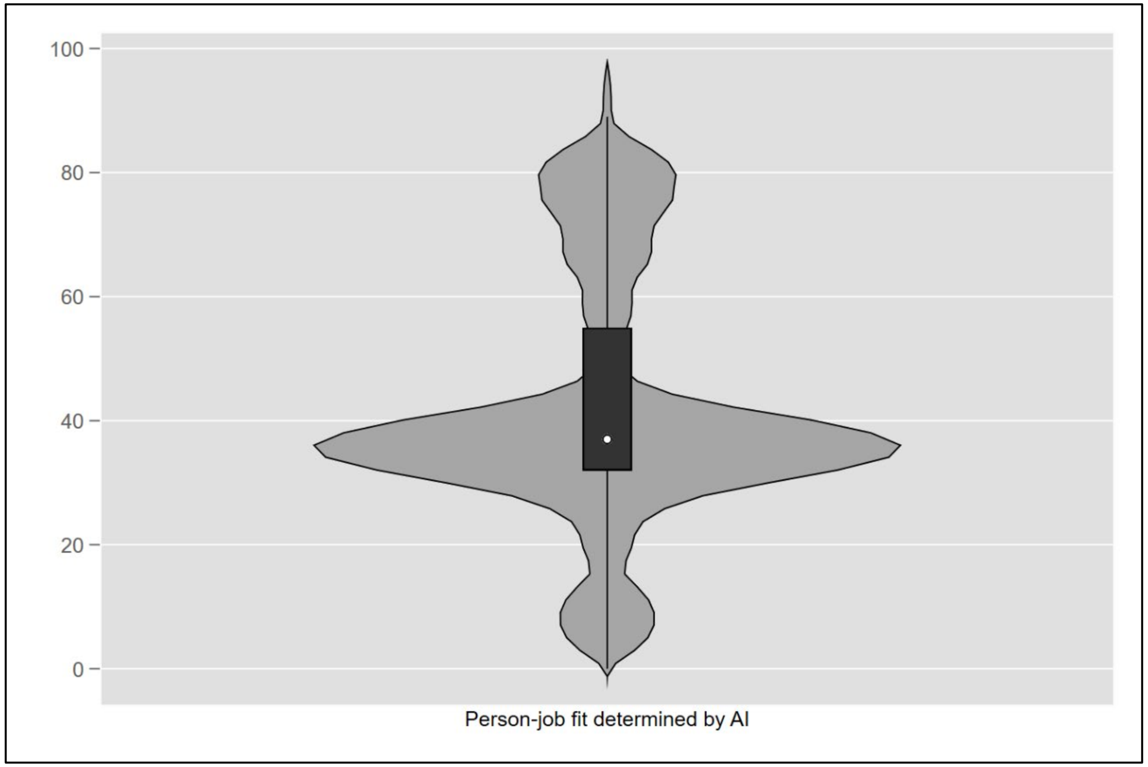


Figure A2: Violin Plot of the Person–job Fit Determined by the AI (in %)



Note for Figures A2-A4: Each of the three plots includes a marker (dot) for the median, a box indicating the interquartile range, and spikes extending to the upper- and lower-adjacent values as in standard box plots. This is overlaid with a univariate kernel density estimation.

Figure A3: Violin Plot of the Person–job Fit Determined by the Leaders (in %)

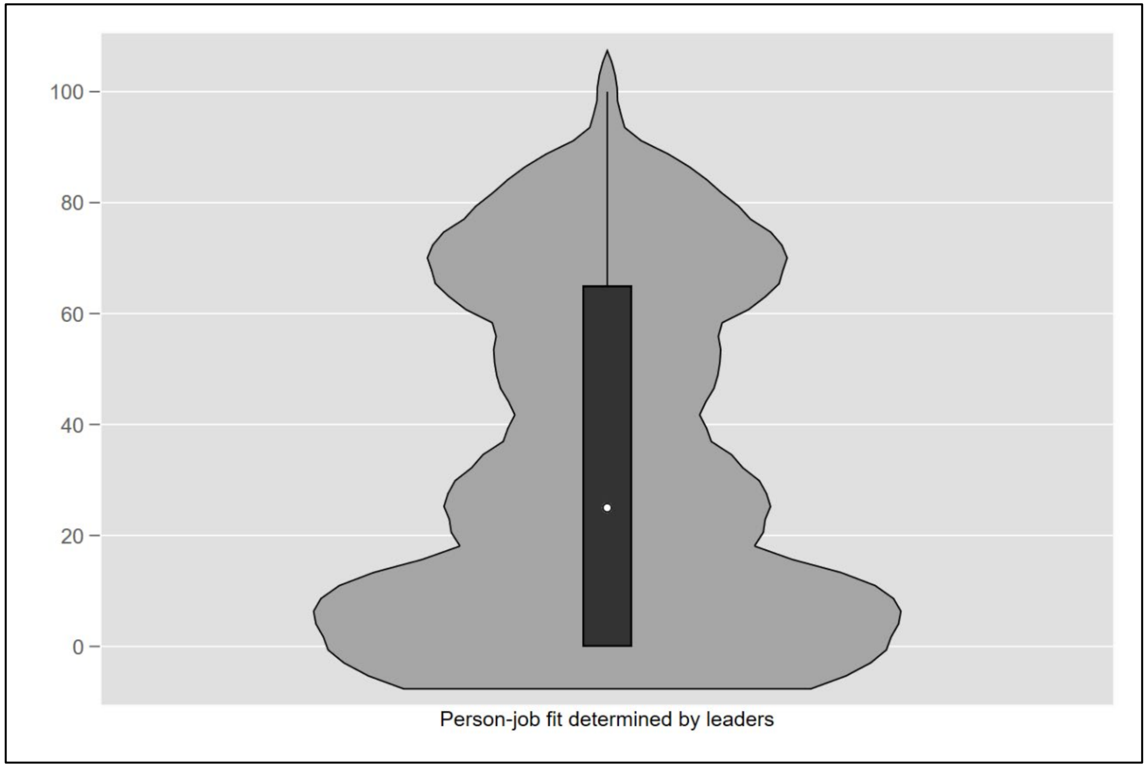


Figure A4: Violin Plot of the Difference Between the Person–job Fit Determined by AI and Leaders (in %)

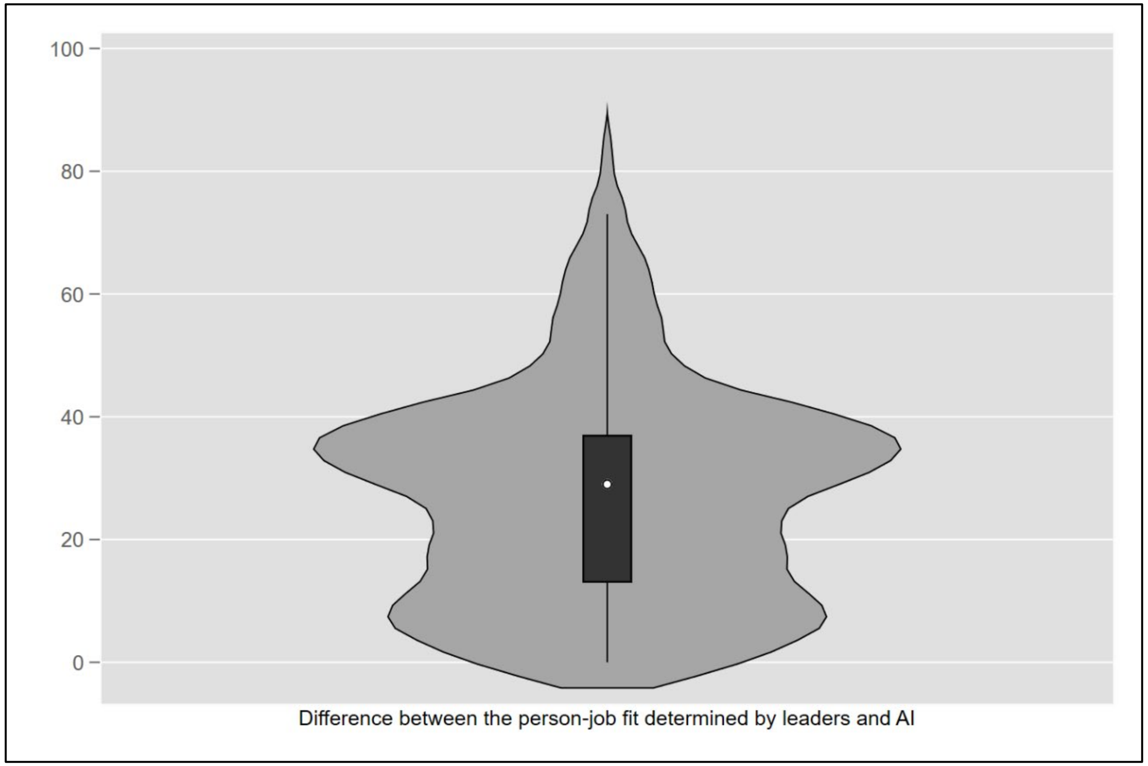


Table A1: Translated Versions of the Direct Sourcing Messages for the Experimental Groups (Treatment Variations Highlighted in Bold Print)

Control	Treatment Human	Treatment AI	Treatment Human + AI
You are convincing, [Ms. Last Name]! Dear [Ms. Last Name], in our search for a new team member, we came across you because you are well versed in [job title 1/2/3]. Looking at your profile, we believe that you may be an excellent fit for us.	You are convincing our team, [Ms. Last Name]! Dear [Ms. Last Name], in our search for a new team member, we came across you because you are well versed in [job title 1/2/3]. Looking at your profile, we believe that you may be an excellent fit for us. This has been identified by our recruitment team. Our recruitment team has searched profiles on Xing and identified that you could be a valuable team member.	You are convincing our AI, [Ms. Last Name]! Dear [Ms. Last Name], in our search for a new team member, we came across you because you are well versed in [job title 1/2/3]. Looking at your profile, we believe that you may be an excellent fit for us. This has been identified by our recruitment software, which is based on artificial intelligence. Our recruitment AI searched profiles on Xing and identified that you could be a valuable team member.	You are convincing us & our AI, [Ms. Last Name]! Dear [Ms. Last Name], in our search for a new team member, we came across you because you are well versed in [job title 1/2/3]. Looking at your profile, we believe that you may be an excellent fit for us. This has been identified by our recruitment team with our recruiting software, which is based on artificial intelligence. With the support of AI, our recruitment team has searched profiles on Xing and identified that you could be a valuable team member.
Please feel free to reply to our message if you are also interested in further personal contact. We at Stadtwerke Heidelberg really offer meaningful jobs. With us, work and private life are in balance. Our team goes home in the evening with a good feeling. Best regards to [place of residence]! [Female/male recruiter - random] Human Resources Management Stadtwerke Heidelberg GmbH	Please feel free to reply to our message if you are also interested in further personal contact. We at Stadtwerke Heidelberg really offer meaningful jobs. With us, work and private life are in balance. Our team goes home in the evening with a good feeling. Best regards to [place of residence]! [Female/male recruiter - random] Human Resources Management Stadtwerke Heidelberg GmbH	Please feel free to reply to our message if you are also interested in further personal contact. We at Stadtwerke Heidelberg really offer meaningful jobs. With us, work and private life are in balance. Our team goes home in the evening with a good feeling. Best regards to [place of residence]! [Female/male recruiter - random] Human Resources Management Stadtwerke Heidelberg GmbH	Please feel free to reply to our message if you are also interested in further personal contact. We at Stadtwerke Heidelberg really offer meaningful jobs. With us, work and private life are in balance. Our team goes home in the evening with a good feeling. Best regards to [place of residence]! [Female/male recruiter - random] Human Resources Management Stadtwerke Heidelberg GmbH

Table A2: Mean, Standard Deviation (in Parentheses), and Tests for Group Differences for all Four Experimental Groups

Variable	Control	Human	AI	Human + AI	F-value/ Chi²	p-value
Female	.261 (.440)	.268 (.443)	.270 (.444)	.276 (.448)	.100	.963
Public sector	.281 (.450)	.285 (.452)	.287 (.453)	.292 (.455)	.005	.987
Distance (in km)	197.084 (98.355)	194.417 (97.448)	197.306 (98.893)	202.681 (98.317)	.630	.595
Employment duration (in month)	57.508 (58.246)	58.441 (63.621)	56.294 (54.383)	57.447 (54.296)	.110	.957
Female recruiter	.498 (.501)	.50 (.501)	.498 (.500)	.504 (.500)	.047	.997
Person–job fit determined by leader	33.292 (31.605)	34.049 (29.949)	37.359 (32.994)	35.384 (33.262)	.520	.671
Person–job fit determined by AI	43.284 (21.533)	41.931 (20.744)	41.232 (20.008)	42.325 (20.167)	.850	.465
Openness to move determined by AI	17.117 (5.719)	17.290 (6.295)	16.698 (5.665)	17.189 (5.630)	1.000	.392
Openness to job change determined by AI	45.381 (10.469)	44.849 (10.378)	44.732 (10.560)	44.805 (10.650)	.390	.760

Table A3: Summary Statistics for All Experimental Groups

Experimental group		Control						AI					
Variable	Type	Obs.	Mean	S.D.	Median	Min.	Max.	Obs.	Mean	S.D.	Median	Min.	Max.
Response to message	Binary	486	0.226	0.419	0	0	1	504	0.198	0.399	0	0	1
Interest in the job	Binary	110	0.455	0.500	0	0	1	100	0.230	0.423	0	0	1
Length of reply (in characters)	Numeric	110	270.973	176.150	222.5	17	1,036	100	259.020	176.912	233.5	0	959
Number of clicks	Numeric	110	1.682	2.633	0	0	14	504	100	1.080	0	0	12
Click	Binary	110	0.373	0.486	0	0	1	504	100	0.230	0	0	1
Female	Binary	486	0.261	0.440	0	0	1	504	0.270	0.444	0	0	1
Public sector	Binary	480	0.281	0.450	0	0	1	492	0.287	0.453	0	0	1
Distance (in km)	Numeric	486	197.084	98.355	234.5	0	400	504	197.306	98.893	220.5	0	391
Employment duration (in month)	Numeric	455	57.508	58.246	39	2	382	469	56.294	54.383	38	1	338
Female recruiter	Binary	486	0.498	0.501	0	0	1	504	0.498	0.500	0	0	1
Person–job fit determined by leader	Percent	168	33.292	31.605	25	0	100	167	37.359	32.994	40	0	100
Person–job fit determined by AI	Percent	486	43.284	21.533	37	0	95	504	41.232	20.008	36	1	95
Openness to move determined by AI	Percent	486	17.117	5.719	15	5	35	504	16.698	5.665	15	1	35
Openness to job change determined by AI	Percent	486	45.381	10.469	45	5	65	504	44.732	10.560	45	5	65
Experimental group		Human						Human + AI					
Response to message	Binary	496	0.204	0.403	0	0	1	514	0.202	0.402	0	0	1
Interest in the job	Binary	101	0.307	0.464	0	0	1	104	0.288	0.455	0	0	1
Length of reply (in characters)	Numeric	101	239.614	179.728	196	18	933	104	241.414	187.793	195	17	840
Number of clicks	Numeric	101	1.079	2.171	0	0	12	104	0.990	1.835	0	0	8
Click	Binary	101	0.230	0.434	0	0	1	104	0.250	0.435	0	0	1
Female	Binary	496	0.268	0.443	0	0	1	514	0.276	0.448	0	0	1
Public sector	Binary	485	0.285	0.452	0	0	1	497	0.292	0.455	0	0	1
Distance (in km)	Numeric	496	194.417	97.448	227	0	389	514	202.681	98.317	241	0	381
Employment duration (in month)	Numeric	442	58.441	63.621	37	1	482	470	57.447	54.296	43	1	457
Female recruiter	Binary	496	0.500	0.501	0.5	0	1	514	0.504	0.500	1	0	1
Person–job fit determined by leader	Percent	162	34.049	29.949	25	0	100	198	35.384	33.262	25	0	100
Person–job fit determined by AI	Percent	496	41.931	20.744	36	0	93	514	42.325	20.167	37	0	95
Openness to move determined by AI	Percent	496	17.290	6.295	15	5	61	514	17.189	5.630	15	5	40
Openness to job change determined by AI	Percent	496	44.849	10.378	45	5	65	514	44.805	10.650	45	5	65

Table A4: Correlation Matrix Overall and For the Three Job-Specific Subsamples

Overall	Variable	1	2	3	4	5	6	7	8	9
1	Female	-								
2	Public sector	.041 (.069)	-							
3	Distance (in km)	-.025 (.274)	.007 (.758)	-						
4	Employment duration (in month)	-.057 (.016)	-.043 (.067)	-.008 (.733)	-					
5	Female recruiter	-.002 (.920)	-.010 (.673)	-.023 (.307)	.026 (.258)	-				
6	Person–job fit determined by leader	-.064 (.090)	.013 (.741)	-.133 (.000)	-.029 (.460)	-.101 (.008)	-			
7	Person–job fit determined by AI	.011 (.633)	-.150 (.000)	-.009 (.694)	.047 (.044)	-.041 (.065)	.323 (.000)	-		
8	Openness to move determined by AI	.029 (.193)	-.111 (.000)	-.072 (.001)	-.112 (.000)	.043 (.057)	-.022 (.558)	-.025 (.270)	-	
9	Openness to job change determined by AI	.000 (.986)	.038 (.095)	-.028 (.209)	-.284 (.000)	-.050 (.026)	.036 (.339)	-.022 (.318)	.069 (.002)	-
Job 1: Finance app. specialist										
1	Female	-								
2	Public sector	.048 (.253)	-							
3	Distance (in km)	.043 (.288)	.027 (.520)	-						
4	Employment duration (in month)	-.027 (.527)	-.048 (.268)	-.033 (.448)	-					
5	Female recruiter	-.030 (.470)	.004 (.925)	-.066 (.109)	.027 (.535)	-				
6	Person–job fit determined by leader	.000 (.998)	-.040 (.544)	-.016 (.802)	-.059 (.387)	-.068 (.296)	-			
7	Person–job fit determined by AI	-.116 (.004)	-.083 (.047)	.034 (.410)	.043 (.313)	-.060 (.146)	.717 (.000)	-		
8	Openness to move determined by AI	.095 (.020)	-.067 (.110)	-.030 (.469)	-.171 (.000)	-.034 (.409)	-.096 (.137)	-.082 (.044)	-	
9	Openness to job change determined by AI	.036 (.382)	.045 (.283)	-.024 (.556)	-.292 (.000)	-.024 (.556)	.001 (.985)	-.030 (.461)	.134 (.001)	-

Note: Pearson correlations are displayed, followed by p-values (in parentheses).

Table A4 (continued)

Job 2: Utility app. specialist	1	2	3	4	5	6	7	8	9
1 Female	-								
2 Public sector	.106 (.001)	-							
3 Distance (in km)	-.040 (.203)	-.034 (.289)	-						
4 Employment duration (in month)	-.045 (.177)	-.065 (.050)	-.031 (.349)	-					
5 Female recruiter	.039 (.217)	-.005 (.887)	.011 (.737)	.026 (.427)	-				
6 Person–job fit determined by leader	-.064 (.322)	-.098 (.131)	-.248 (.000)	.119 (.075)	-.012 (.848)	-			
7 Person–job fit determined by AI	-.047 (.138)	-.045 (.160)	.003 (.933)	.062 (.060)	.035 (.268)	.268 (.000)	-		
8 Openness to move determined by AI	-.023 (.460)	-.100 (.002)	-.090 (.004)	-.072 (.029)	.072 (.023)	.082 (.202)	-.052 (.103)	-	
9 Openness to job change determined by AI	-.036 (.256)	.043 (.175)	-.026 (.406)	-.269 (.000)	-.041 (.194)	-.006 (.926)	-.028 (.380)	.040 (.202)	-
Job 3: Team leader power grid									
1 Female	-								
2 Public sector	.060 (.236)	-							
3 Distance (in km)	-.063 (.211)	.004 (.925)	-						
4 Employment duration (in month)	-.134 (.009)	-.028 (.589)	.074 (.149)	-					
5 Female recruiter	-.059 (.238)	-.056 (.270)	-.052 (.305)	.027 (.601)	-				
6 Person–job fit determined by leader	-.101 (.144)	.363 (.000)	-.071 (.302)	-.126 (.073)	-.331 (.000)	-			
7 Person–job fit determined by AI	.024 (.629)	.245 (.000)	.035 (.480)	.083 (.105)	-.141 (.005)	.215 (.002)	-		
8 Openness to move determined by AI	-.006 (.899)	-.082 (.104)	-.073 (.144)	-.100 (.051)	.098 (.051)	.008 (.909)	-.210 (.000)	-	
9 Openness to job change determined by AI	.021 (.673)	.099 (.050)	-.017 (.741)	-.306 (.000)	-.108 (.031)	.120 (.082)	-.083 (.099)	.031 (.539)	-

Note: Pearson correlations are displayed, followed by p-values (in parentheses).

Table A5: Linear Regression Analysis on the Person–job Fit Determined by the Leader for the Three Job-Specific Subsamples

	Job 1: Finance app. specialist		Job 2: Utility app. specialist		Job 3: Team leader power grid	
Variables	1	2	3	4	5	6
Person–job fit	1.462 (.000)	1.497 (.000)	.910 (.000)	.830 (.000)	.277 (.004)	.304 (.003)
determined by AI	.081	.089	.149	.159	.095	.100
Openness to move		-.384 (.212)		.046 (.902)		.122 (.621)
determined by AI		.307		.374		.247
Openness to job change		.079 (.687)		.054 (.781)		.133 (.330)
determined by AI		.196		.194		.136
Female		7.268 (.115)		-1.719 (.668)		-12.111 (.003)
		4.586		4.007		3.959
Public sector		-2.995 (.708)		-3.411 (.356)		13.156 (.000)
		7.972		3.685		3.004
Distance		.018 (.424)		-.065 (.002)		-.008 (.579)
		.022		.021		.014
Employment duration		-.063 (.082)		.063 (.110)		-.055 (.038)
		.036		.039		.026
Constant	-43.956 (.000)	-43.628 (.002)	-10.339 (.079)	1.282 (.931)	37.267 (.000)	30.569 (.002)
	4.440	14.011	5.871	14.704	2.248	9.954
Observations	240	210	244	225	211	201
R-squared	0.514	0.528	0.072	0.142	0.046	0.205

Note: This table shows the relationship between the person–job fit determined by the AI application and the leaders. Beta-coefficients are displayed, followed by p-values (in parentheses) and robust standard errors.

Table A6: Linear Regression Analysis on the Person–job Fit Determined by the AI Application

Variables	Overall	Job 1: Finance app. specialist	Job 2: Utility app. specialist	Job 3: Team leader power grid
Openness to move determined by AI	-.032 (.718) .090	-.153 (.314) .151	-.080 (.319) .080	-.404 (.020) .174
Openness to job change determined by AI	-.003 (.958) .047	-.002 (.984) .084	-.013 (.763) .042	-.166 (.068) .091
Female	.951 (.376) 1.075	-5.072 (.006) 1.828	-1.038 (.269) .939	1.532 (.574) 2.722
Public sector	-6.786 (.000) .976	-7.365 (.098) 4.441	-.860 (.320) .864	10.115 (.000) 2.214
Distance	-.004 (.408) .005	.006 (.542) .009	-.003 (.532) .004	.008 (.457) .010
Employment duration	.014 (.097) .008	.007 (.579) .013	.011 (.194) .008	.020 (.238) .017
Constant	43.695 (.000) 3.052	61.155 (.000) 5.092	41.744 (.000) 2.727	30.850 (.000) 6.253
Observations	1,806	526	903	377
R-squared	0.025	0.026	0.007	0.091

Note: This table shows the relationship between the person–job fit determined by the AI application and the control variables. The regressions in columns 2, 3, and 4 present the results for the job-specific subsamples. Beta-coefficients are displayed, followed by p-values (in parentheses) and robust standard errors.

Table A7: Linear Regression Analysis—Impact of Treatment on the Response to the Direct Sourcing Message and the Click in the Second Message

Variables	Response				Click on link to career page			
	1	2	3	4	5	6	7	8
Human	-.023 (.849) .026	-.014 (> .999) .028	-.057 (.546) .033	-.008 (> .999) .031	-.125 (.098) .063	-.129 (.270) .064	-.072 (> .999) .073	-.134 (.860) .078
AI	-.028 (.849) .026	-.020 (> .999) .027	-.041 (.692) .033	-.007 (> .999) .031	-.143 (.069) .063	-.114 (.345) .063	-.027 (> .999) .071	-.124 (.954) .077
Human + AI	-.024 (.849) .026	-.029 (> .999) .027	-.056 (.546) .032	-.020 (> .999) .031	-.123 (.098) .063	-.102 (.476) .065	-.035 (> .999) .073	-.083 (> .999) .080
Female		-.025 (> .999) .022	-.112 (.054) .041	-.025 (> .999) .022		-.039 (> .999) .050	.245 (.336) .124	-.040 (> .999) .050
Public sector		.084 (.000) .023	.084 (.000) .023	.108 (.210) .047		.102 (.210) .047	.099 (.272) .047	.104 (> .999) .097
Distance		.000 (> .999) .000	.000 (.720) .000	.000 (> .999) .000		-.001 (.000) .000	-.001 (.011) .000	-.001 (.000) .000
Employment duration		-.001 (.000) .000	-.001 (.000) .000	-.001 (.000) .000		.000 (> .999) .000	.000 (> .999) .000	.000 (> .999) .000
Female recruiter		.012 (> .999) .019	.012 (.720) .019	.012 (> .999) .019		-.037 (> .999) .044	-.037 (> .999) .044	-.036 (> .999) .044
Female x Human			.163 (.064) .062				-.303 (.336) .153	
Female x AI			.080 (.692) .059				-.440 (.030) .147	
Female x Human + AI			.103 (.546) .059				-.345 (.252) .157	
Public sector x Human				-.019 (> .999) .066				.014 (> .999) .135
Public sector x AI				-.046 (> .999) .064				.029 (> .999) .133
Public sector x Human + AI				-.032 (> .999) .064				-.052 (> .999) .137
Constant	.226 (.000) .019	.260 (.000) .034	.287 (.000) .036	.254 (.000) .035	.373 (.000) .046	.538 (.000) .072	.469 (.000) .077	.538 (.000) .078
Observations	2,000	1,806	1,806	1,806	415	390	390	390
R-squared	0.001	0.018	0.022	0.019	0.017	0.076	0.099	0.077

Note: The regressions in columns 3, 4, 7, and 8 assess the interaction between treatment arms and gender and current affiliation to the public sector, respectively. Beta-coefficients are displayed, followed by p-values (in parentheses, Holm-Bonferroni corrected) and robust standard errors.

Table A8: Linear Regression Analysis on the Openness to Job Change and Openness to Move Determined by the AI Application

Variables	Openness to move determined by AI	Openness to job change determined by AI
Female	.381 (.237) .322	-.448 (.427) .563
Public sector	-1.424 (.000) .297	.650 (.236) .548
Distance	-.004 (.003) .001	-.003 (.188) .002
Employment duration	-.011 (.000) .002	-.054 (.000) .004
Constant	19.091 (.000) .364	48.566 (.000) .655
Observations	1,806	1,806
R-squared	0.030	0.082

Note: This table shows the relationship between the openness to job change and openness to move determined by the AI application and the control variables. Beta-coefficients are displayed, followed by p-values (in parentheses) and robust standard errors.