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Mixed signals? A receiver-centric perspective on the interpretation of algorithmic control signals

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ABSTRACT

Organizational control fundamentally changes when algorithms are used to automate or augment control functions. Here, we construe organizations' use of algorithmic control as a signal to potential applicants about the organization's reputation. Drawing on signaling theory, we suggest a receiver-centric approach to the interpretation of algorithmic control signals. More specifically, we argue that individuals' lay beliefs about Artificial Intelligence (AI) affect how they infer organizational values from the degree of algorithmic control, such that individuals who are more skeptical (vs. optimistic) about AI are more likely to interpret algorithmic control as a negative (vs. a positive) signal, which in turn relates to individuals' intention to accept a job offer. We test our model with two experimental studies ($N = 402$ and $N = 440$). As expected, lay beliefs about AI moderated the indirect effects of higher degrees of algorithmic control on the job acceptance intention *via* perceived trust in employees, and the bias and consistency factor of procedural justice, but not *via* the voice and morality factor of procedural justice. Implications for HRM scholars and practitioners are discussed.

KEYWORDS

Algorithmic control; algorithmic HRM; artificial intelligence; organizational control; signaling theory; lay beliefs about AI; organizational values

1. Introduction

Organizational control is a traditionally manager-centric process that ensures employees behave in ways that benefit the organization's goals (Cardinal et al., 2017). The use of HRM-related algorithms, defined as automated systems that use data to augment or automate HR-related decisions (Meijerink et al., 2021), offers opportunities for organizations to automate (parts of) organizational control to increase productivity and

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efficiency (Kellogg et al., 2020). Here, we focus on algorithmic (organizational) control, which is increasingly used by organizations to streamline HR processes. For example, algorithmic control finds its application in HR practices, not only in the platform context but also in more traditional forms of organizations through influencing and directing employee actions toward desired organizational outcomes. Performance management systems often use algorithms to evaluate employee productivity and behavior, relying on metrics like sales figures or customer feedback. These algorithms may affect bonuses, disciplinary actions, or suggest trainings based on performance data. According to a study of 250 HR leaders, 72% were using AI for performance management amongst other HR practices (Eightfold AI, 2022), which shows that algorithmic control is finding its way into HRM. By quantifying behavior and performance, algorithms can make previously implicit processes explicit (Schafheitle et al., 2020), which changes the manager-employee relationship and creates new challenges for HRM (Leicht-Deobald et al., 2019).

Previous research has shown that the use of algorithmic control can lead to a variety of employee reactions (see Langer & Landers, 2021 for an overview). Yet, as organizations decide to deploy algorithms to automate or augment control functions, it is important to consider not only how current employees respond but also how such practices are perceived by potential employees. Organizational practices, such as algorithmic control, can send powerful signals to external audiences (Guest et al., 2021). For example, Amazon's use of algorithmic control in its warehouses, including real-time productivity tracking and automated disciplinary systems, has been widely discussed in the media (Hanley & Hubbard, 2020). Prospective applicants often form impressions of employers through publicly available information, media coverage, and online reviews (Lange et al., 2011), which can shape their perceptions of the work environment. In this way, algorithmic control systems may signal key aspects of the employment relationship to job seekers, which can influence their decisions to apply or not. In today's competitive labor market, where attracting top talent is critical, it is important for organizations to consider how control practices are interpreted externally and the broader signaling effects they may produce.

Signaling theory (Spence, 1973) is centered around the idea of information asymmetry between two parties. One party holds information that the other party needs to make a decision, and signals can reduce information symmetry. In line with this, individuals use available information about an organization and interpret this information as a signal of organizational characteristics (Ehrhart & Ziegert, 2005). Here, we focus on the information asymmetry between applicants and a hiring target organization to explore the signaling effects of algorithmic control.

HR plays an important role in promoting the employer brand and reputation (Cascio & Graham, 2016). Although applicants are not in contact with specific control practices yet, information about an organization's use of algorithmic control can be used as a signal by job seekers and predict applicants' attraction to an organization (Stockman et al., 2020; Van Hoye & Lievens, 2009). Signaling theory suggests that not all signals are intentional (Connelly et al., 2011), as certain organizational practices, such as the use of algorithmic control, can send unintentional signals to individuals (Ehrhart & Ziegert, 2005).

Here, we adopt a receiver-centric perspective on the signaling process. We consider both the manifestation of algorithmic control in an organization and the role of potential applicants' underlying beliefs about artificial intelligence (AI) in shaping signal interpretation. (Block & Funder, 1986). We argue that the assumption that signals are interpreted in isolation without considering individual characteristics may result in incomplete understanding. Signaling theory emphasizes that receivers with different characteristics can interpret the same signal differently (Burbano, 2016; Connelly et al., 2011). Signal receivers may assign varying degrees of significance to signals based on domain-specific preexisting beliefs about their importance (Ehrhart & Ziegert, 2005). Therefore, we focus on individuals' pre-existing lay beliefs about AI, which refer to perceptions, opinions, and attitudes held by individuals about the capabilities of AI in different areas.

Lay beliefs about AI may be especially relevant in a context where individuals have not experienced the control practices themselves, but instead have to rely on the limited organizational information available to them in combination with their existing beliefs about AI (von Walter et al., 2022). We thus examine how lay beliefs about AI act as a boundary condition to the interpretation of algorithmic control signals. More specifically, since signal receivers use all available information about organizations to infer symbolic intangible organizational traits such as organizational values (Lievens and Highhouse, 2003), we suggest that the same signal, the degree of algorithmic control (operationalized by four levels ranging from non-algorithmic control over two levels of augmented control to full algorithmic control), can be perceived as a positive or negative organizational value signal depending upon the receiver's lay beliefs and affect an applicants' decision to accept a job offer. The same signal can thus be interpreted differently depending on preexisting lay beliefs.

The organizational control literature emphasizes that trust is a value easily affected by organizational control, such that it can either be promoted (Verburg et al., 2018) or it can be harmed when control is perceived as coercive (Bijlsma-Frankema & Costa, 2010). While applicants

cannot make a judgment about organizational trust yet, they may infer how much an organization trusts theirits employees based on the algorithmic control practices implemented at the organization. We suggest that the inferred level of trust in employees acts as a signaling mechanism linking the interactive effect of the degree of algorithmic control and lay beliefs about AI to intention to accept a job offer. To test our model, we ran two experimental studies. Based on an additional qualitative inquiry in Study 1 and further theorizing, we include procedural justice as an additional signaling mechanism to our model in Study 2.

The present article aims to make several contributions: We apply signaling theory to the context of algorithmic control to propose that an organization's use of algorithmic control acts as a signal of the values implemented at the organization. However, by highlighting the receiver's role in the algorithmic control signaling process, we suggest that a signal is not interpreted in isolation, but always conjointly with pre-existing beliefs that an individual holds. We propose that individuals who are skeptical (vs. positive) about AI are more likely to interpret algorithmic control as a negative (vs. positive) signal of the organization's values. Finally, we advance the work on algorithmic control by testing potential mechanisms that link algorithmic control signals and applicant intentions. More specifically, we test to what extent individuals use their beliefs about AI to interpret the degree of algorithmic control as a signal of how much an organization trusts its employees and of how procedurally just an organization is likely to be. We suggest that those inferred organizational values act as parallel signaling mechanisms that predict the intention to accept a job offer.

2. Theoretical background & hypotheses development

2.1. Algorithmic control

According to Cardinal et al. (2010), organizational control refers to the systems and processes organizations use to ensure their operations align with their objectives, and it involves monitoring, measuring, and evaluating performance. It also involves influencing employee motivation through goal-setting, feedback, and recognition (Cardinal et al., 2017). Control can impact employee motivation positively when exercised fairly, transparently, and respectfully (Long et al., 2011). However, heavy-handed or coercive control can lead to stress and mistrust among employees (Adler & Borys, 1996; Weibel et al., 2016). Two primary forms of control are output control and behavioral control. Output control involves measuring the quantity and quality of employees' work, whereas behavioral control monitors and regulates employees' behavior to ensure compliance with organizational rules and policies (Snell, 1992).

Within the broader category of algorithmic management, the delegation of core managerial functions to algorithmic systems, algorithmic control has emerged as an increasingly widespread practice. Algorithmic management encompasses various functions such as performance evaluation, scheduling, compensation, and even termination, often carried out with limited human oversight (Parent-Rocheleau & Parker, 2022). Algorithmic control, as a subset of this broader paradigm, specifically refers to the use of algorithms to augment or automate control functions such as monitoring, providing feedback, evaluating performance, and sanctioning or rewarding employees' behavior (Kellogg et al., 2020). This provides opportunities to make organizational control more efficient and fair (Schafheitle et al., 2020). Algorithmic control relies on technology and data to manage employee behavior, while in contrast, traditional organizational control and bureaucratic control rely more on hierarchical structures, rules, and procedures (Cardinal et al., 2017). Algorithmic control is "more comprehensive, instantaneous, interactive, and opaque" (Kellogg et al., 2020; p.396) than traditional control because algorithms can quantify, record, and analyze employees' behavior and performance in real-time and make it more transparent to the organization (Bernstein, 2017). For example, an algorithmic performance management system enables managers to track employees' performance continuously and thoroughly.

Algorithmic control exists on a spectrum, with varying degrees of automation to human control. Kellogg et al. (2020) identify three levels: direction, evaluation, and discipline. Parent-Rocheleau et al. (2024) break down algorithmic management into five distinct components: control, evaluation, interaction, support, and optimization. Within this framework, algorithmic control is defined as the extent to which algorithms are used to direct and constrain employee behavior. Building on this literature, our contribution lies in conceptualizing algorithmic control more explicitly as a form of organizational control and in theorizing its degrees of intensity. We adapt Snell's (1992) classic framework of control—monitoring, evaluating and providing feedback, and rewarding or sanctioning—as a way to operationalize and scale the degree of algorithmic involvement in control functions. At the first level, all control functions are performed by a human manager. The second and third degrees of control constitute augmented approaches to control. Augmentation refers to a collaboration between humans and algorithms to perform a task (Raisch & Krakowski, 2021). Therefore, we translate augmentation of control into a distribution of task responsibilities between humans and algorithmic systems. We distinguish between low augmentation (monitoring is automated, whereas a human manager performs the other functions) and high augmentation (monitoring, evaluation and feedback are

automated, whereas rewarding or sanctioning is performed by a human manager). Finally, all control functions are automated in the fourth degree of control, referred to as full algorithmic control.

2.2. A signaling perspective on algorithmic control

According to the proxy view of technology (Kim et al., 2021), individuals' cognitive and behavioral responses to technology determine its impact (Orlikowski & Iacono, 2001). Consequently, the meaning of the technology is shaped by individuals' interpretation of the technology. Much of the literature on algorithmic control focuses on how it is experienced by workers on gig-working platforms or employees in organizations, for example, in terms of fairness (Köchling & Wehner, 2020), autonomy (Wood et al., 2019), trust (Glikson & Woolley, 2020), and well-being (Kinowska & Sienkiewicz, 2023). However, research has neglected to consider how individuals react to organizations' use of algorithmic control when they are not yet a member of said organization but are evaluating the organization as a potential employer. We argue that this perspective deserves more attention as HR is important in building and protecting the employer brand (Cascio & Graham, 2016), yet so far, the reputational effects of algorithmic control on individuals outside of the organization remain unexplored. Connecting this to signaling, we evaluate how potential applicants' interpretation of algorithmic control shapes their attitude toward the organization.

Signaling theory explains how two parties, the signaler and the receiver, communicate and receive information, mainly when the information distribution is asymmetrical, and one party has more information than the other. The idea of "signals" is a key concept in this theory and describes that actions or behaviors convey information about an involved party's characteristics, abilities, or intentions (Connelly et al., 2011). For example, a job candidate might signal their qualifications by presenting good grades on a resume (Celani & Singh, 2011). Similarly, HR practices can form signals to individuals about the organization (Bowen & Ostroff, 2004; Chang & Chin, 2018; Guest et al., 2021). When individuals possess limited information about an organization (e.g., in a job search), the information that is available is used to infer organizational characteristics and inform attitudes toward an organization (Ehrhart & Ziegert, 2005). Organizations can strategically influence signals, for example, by signaling corporate sustainability practices (Zhang et al., 2020). However, the idea of unintentionally signaling organizational values has so far only received little attention in the literature (Connelly et al., 2011). For algorithmic control, unintentional signals are relevant as an organization's decision to implement algorithmic control may be interpreted as a signal

by the receiver, in this case, the applicant. Yet, the received signal may not necessarily align with the sender's (the organization's) intention. We argue that signal interpretation depends both on the signaled degree of algorithmic control and on the characteristics of the signal receiver.

2.2.1. The role of the receiver in the interpretation of algorithmic control signals

Individual differences are critical determinants in attitude formation, and the same social stimulus can be perceived differently by different individuals (Block & Funder, 1986). Highhouse et al. (2007) suggest that to understand why individuals feel attracted to some organizations and not others, it is necessary to turn to the perspective and characteristics of potential applicants. Relating this to signaling theory implies that it is essential to understand the role of the signal receiver and not only the signal sender. More specifically, signaling theory proposes that receivers may weigh or cognitively distort signals based on prior perceptions of their importance so that signals' meanings can differ from the signaler's original purpose (Connelly et al., 2011; Ehrhart & Ziegert, 2005). Previous research shows that individual differences affect signal interpretation (Burbano, 2016). Individuals' beliefs might result in signal receivers attributing different levels of importance to signals (Ehrhart & Ziegert, 2005). To fully understand how algorithmic control signals are received, we need to consider individuals' beliefs as part of the interpretation process. For algorithmic control, this distortion may be especially pronounced for domain-specific beliefs,thus, beliefs about automation and artificial intelligence (AI).

Lay beliefs about AI cover beliefs individuals hold about the different types of capabilities (e.g., analytical or socio-emotional skills) and the overall intelligence of AI in comparison to human intelligence (von Walter et al., 2022). When evaluating algorithmic control, lay beliefs about AI become relevant due to their influence on individuals' perceptions, attitudes, and decision-making processes. Lay beliefs about AI may shape how people understand and interpret the outcomes produced by algorithms. For instance, individuals with optimistic beliefs about the capabilities of AI may interpret algorithmic control more positively, while those with pessimistic beliefs may view it with skepticism. This notion aligns with the two major directions present in the literature: algorithmic aversion, rejecting algorithmic decisions in favor of human decisions (see Mahmud et al., 2022), and algorithmic appreciation, favoring algorithmic input (Logg et al., 2019). Thus, when individuals lack firsthand experience with the organization's approach to algorithmic control and possess limited information, lay beliefs about AI could be particularly pertinent in shaping the interpretation of algorithmic control signals. Jointly, lay

beliefs about AI and information about algorithmic control may shape how potential applicants form opinions about the organization's attractiveness, because individuals use all available information about an organization and their own beliefs to infer not only instrumental attributes (e.g., salary) but also symbolic intangible traits such as organizational values (Lievens and Highhouse, 2003).

Organizational values are at the core of every organization and guide decision-making and actions (Van der Wal et al., 2006). They may differ based on factors such as industry, public vs. private sector, or company size (Van Der Wal et al., 2008). One value central to the organization-employee relationship is trust. Trust is at the center of any relationship and is a reciprocal construct that involves the trustor and the trustee (Axelrod & Hamilton, 1981). The organizational control literature indicates that when implemented well, organizational control can signal trust (Verburg et al., 2018), whereas when control practices are perceived as coercive, they can be interpreted as a signal of distrust by the organization (Bijlsma-Frankema & Costa, 2010). However, while potential applicants are not yet affected by the organization's algorithmic control, they will pick up on the form of control as a signal of how much an organization trusts its employees. A perception of over-exercise of monitoring and control can be damaging to an organization's reputation and employer brand (Bernstrøm & Svare, 2017). For example, Amazon has repeatedly attracted negative media attention for using excessive (algorithmic) control with networks of security cameras that track employees' movements and algorithmic systems that monitor and optimize employees' task completion (Hanley & Hubbard, 2020), which signals distrust in employees.

In a process where individuals are forming an opinion about the organization's values, the level of inferred trust in employees has been a blind spot in the literature. Individuals want to feel trusted by their future employers (Lau et al., 2014). Thus, based on signaling theory which suggests that HR practices can be interpreted as a signal (Bowen & Ostroff, 2004; Connelly et al., 2011; Guest et al., 2021), we propose that algorithmic control in HR practices is likely to form a signal to applicants because an information asymmetry about the actual organization's values exists for individuals outside of the organization and they are therefore more likely to use any provided information as a signal. However, we argue that algorithmic control does not have a uniform signaling effect across all individuals and therefore do not hypothesize a main effect of algorithmic control. Instead, we propose that under conditions of information asymmetry, individuals rely not only on the signal itself (i.e., algorithmic control practices) but also on their characteristics and assumptions (lay beliefs about AI) to interpret what the signal implies (Connelly et al., 2011). Thus, we propose that

algorithmic control does not signal trust or distrust by the organization for everyone equally, but instead, its interpretation depends on how the individual receives the signal. Individuals' existing lay beliefs about AI determine the interpretation of the signal, such that individuals who are skeptical about AI are more likely to perceive algorithmic control as a signal of the organization not trusting employees, whereas those who are positive about AI do not.

Hypothesis 1: *The effect of the degree of algorithmic control on perceived trust in employees is moderated by individuals' lay beliefs about AI, such that individuals who are skeptical about AI (vs. positive) are more likely to interpret higher degrees of algorithmic control as a signal of low trust in employees.*

2.3. Linking perceived trust in employees to intention to accept a job offer

In turn, we propose that the differential interpretation of organizational values affects individuals' attraction to an organization. Signaling theory proposes that signals of the sender's characteristics directly influence the receiver's actions (Connelly et al., 2011). Thus, when pondering whether to accept or reject a job offer from an organization, inferred organizational values can affect attraction and guide decision-making (Highhouse et al., 2007), in this case, the decision whether or not to join an organization. Inferred organizational values can form signaling mechanisms that explain how individuals process signals (Jones et al., 2014). Here, we argue that the inferred level of trust in employees forms a signaling mechanism linking the individual interpretation of algorithmic control based on beliefs about AI and the degree of algorithmic control to an individual's intention to accept a job offer. If individuals perceive the organization to trust employees, they are more likely to accept the job offer, and this level of inferred trust depends on their interpretation of the degree of algorithmic control (see Figure 1 for full model).

Hypothesis 2: *The indirect effect of the degree of algorithmic control on intention to accept the job offer via perceived trust in employees is moderated by individuals' lay beliefs about AI.*

3. Study 1

3.2. Method

3.2.1. Overview of studies

We present the findings of two studies on the signaling of algorithmic control. Study 1 employs a mixed-method approach to explore how individuals' lay beliefs about AI influence their reception of algorithmic control signals. The quantitative component involves a survey-based experiment in which participants are presented with jobs in organizations

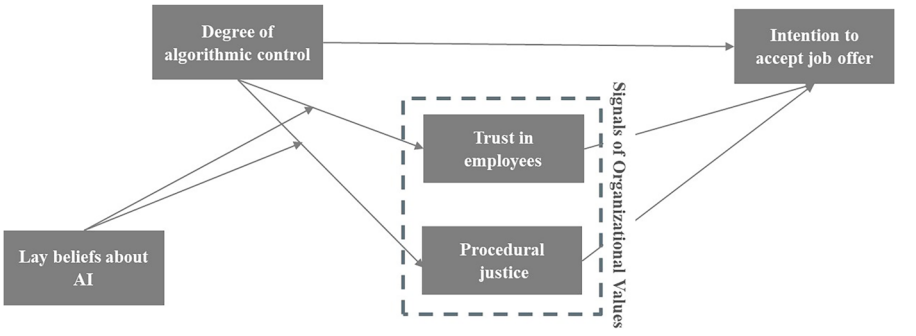


Figure 1. Conceptual model.

employing different levels of algorithmic control and are consequently asked about their perception of the organization employing algorithmic control. Additionally, participants are invited to provide open-text responses to explain their decision for or against the organization.

The mixed-method approach in Study 1 is advantageous for several reasons. First, it allows for a holistic examination of algorithmic control by capturing both numerical data and textual narratives. Our approach enhances the depth of understanding and facilitates triangulation of our findings, thereby increasing the validity and reliability of the study outcomes (Hesse-Biber & Johnson, 2013). In addition, the qualitative analysis of open-text responses enables us to explore nuanced themes that may not be fully captured through quantitative measures alone. By incorporating participants' own expressions, Study 1 aims to uncover a more complete picture of algorithmic control signals. Building upon the insights from Study 1, Study 2 focuses exclusively on quantitative analysis of a survey-based experiment to further examine the signaling mechanisms of algorithmic control, including not only inferred trust but also procedural justice perceptions as mechanisms, based on the findings of Study 1. The sequential design of Study 2 also allows for the validation of findings from Study 1, enhancing the robustness of the overall research conclusions.

3.2.2. Design and sample

In Study 1, we tested our proposed model using a mixed-method approach. More specifically, for our experiment, we used a **4** (degree of algorithmic control) x **2** (target of control)[1] between-subjects design such that each of the eight conditions was represented by a single scenario. Scenario studies are a valuable alternative to classical experiments and nonexperimental studies because of participants' immersion in an organizational scenario instead of participants' assessment of isolated elements (Aguinis & Bradley, 2014). In addition,

experimental realism is increased while independent variables can still be manipulated and controlled, which is especially suitable in new research fields, such as the emerging field of algorithmic control. While we acknowledge the limitations of experiments with regard to external validity, we chose this methodology based on our research question which is focused around signaling effects of algorithmic control. In vignette studies, participants have limited information available about an organization and its approach to HR and therefore are more likely to search for signals. Furthermore, we were specifically interested in prospective employees who were not yet exposed to the organization's algorithmic control.

We recruited participants *via* Prolific (https://www.prolific.co/), an online survey platform producing high-quality data (Douglas et al., 2023; Peer et al., 2022). We prescreened our participants to obtain a UK-native full-time working sample, to ensure that our participants had sufficient working experience to cognitively evaluate the scenarios. As our recruited participants are working full-time they have likely experienced several job application processes and can therefore immerse themselves well into an application scenario where they make judgments about a presented potential employing organization. To ensure adequate statistical power, we conducted an a priori power analysis using G*Power (Faul et al., 2007). We aimed to detect a small to medium effect size ($f = 0.20$) with a significance level of $\alpha = 0.05$ and a power of 0.80. Based on these parameters, the analysis indicated that a minimum sample size of $n = 366$ participants would be required for the planned ANCOVA analysis. Our initial sample consisted of 425 individuals. However, after applying our exclusion criteria (we only included participants who provided a response on the outcome measures and passed the attention check), we had a final sample of 402 participants. Of our participants, 140 identified as males (34,8%), 261 as females (64,9%), and one as non-binary (0,2%). Participants' age ranged from 18-68 years ($M = 39.12$, $SD = 11.4$). 34.3% of participants obtained secondary education, 45.5% a bachelor's degree, 17.2% a master's degree, and 3% a Ph.D.

3.2.3. Procedure

Before our study, we obtained ethical approval (reference nr. EC20220 408010445). At the start of the experiment, participants provided informed consent and then read a fictitious scenario in which they were searching for a new job as a sales agent and had a concrete job offer on the table from an organization called InsureX. We chose a sales context as sales are likely to be relatively easy to understand for participants due to their existence in most organizations. Based on the analysis of open-text answers in our pre-test ($N = 97$), we found that participants

showed sufficient understanding of the situation. After the general introduction of the organization and the terms of the offer (participants read that the job offer corresponds to their wishes in terms of pay, vacation time, and benefits, so that we could minimize the influence of such extraneous factors), participants read the condition-specific scenarios. These scenarios detailed information on the algorithmic control system in the form of word-of-mouth by a current employee of InsureX (see supplementary materials). Participants were instructed to take the perspective of a job seeker who had already received an offer from InsureX and was considering whether to accept it. To support their decision-making, participants were given a job preview through a fictional current employee's description of the company's control system. The scenario invited participants to imagine what working at InsureX *would be like* if they accepted the offer, to help them form an impression of the company's approach to managing employees. This future-oriented framing was designed to reflect how applicants commonly engage with job information before making employment decisions. This approach is consistent with prior research showing that job seekers engage in future-oriented cognitive simulation based on organizational cues (e.g., Cable & Judge, 1996; Lievens & Highhouse, 2003; Lievens & Slaughter, 2016). Next, participants answered scales for intention to accept a job offer, perceived trust in employees, lay beliefs about AI, and demographics. We included one attention check, two manipulation checks, and performed an exploratory decision experiment at the end of the study.

3.2.4. Experimental materials

We manipulated the degree of algorithmic control and the target of control. We used Snell's (1992) organizational control dimensions (monitoring, evaluation & feedback, and rewarding or sanctioning) as steps to increase the degree of algorithmic control. With each level, one more control function was automated, creating four degrees of algorithmic control (see Table 1). The degrees of algorithmic control ranged from 1.

Table 1. Factorial design Study 1&2.

		Target of Control	
		Behavior	Output
Degree of algorithmic control a. *Monitor* b. *Evaluate & provide feedback* c. *Reward or sanction*	**Non-algorithmic** *(a–c human)*	Non-algorithmic-Behavior control	Non-algorithmic-Output control
	Low augmentation *(a–automated, b–c human)*	Low augmentation-Behavior control	Low augmentation-Output control
	High augmentation *(a–b automated, c human)*	High augmentation-Behavior control	High augmentation-Output control
	Full algorithmic *(a–c automated)*	Full algorithmic-Behavior control	Full algorithmic-Output control

non-algorithmic control (a human manager performed all control functions) to 2. *low augmentation* (monitoring was automated whereas a human manager performed other control functions) over 3. *high augmentation* (monitoring, evaluation & feedback were automated, a human manager rewarded or sanctioned) to 4. *full algorithmic control* (an algorithm performed all control functions). Our operationalization aimed to stay true to our theoretical framework of control but also introduces the needed level of nuance to studying algorithmic control (Langer & Landers, 2021). For our second factor, we manipulated the target of control, based on the scale used by Weibel et al. (2016): process control was operationalized as controlling employees' behavior at work, and output control was operationalized as controlling employees' work performance.

Before conducting our Study 1, we ran a pre-test ($N = 97$), which indicated that participants could distinguish between the different degrees of algorithmic control and the target of control. For all three questions regarding the degree of algorithmic control, the significant majority of individuals were able to correctly identify who or what was in charge of monitoring ($\chi^2 = 46.52$, $p < 0.001$), evaluation & feedback ($\chi^2 = 69.29$, $p < 0.001$), as well as rewarding or sanctioning ($\chi^2 = 81.78$, $p < 0.001$). As for the target of control, out of the 47 individuals in the behavioral control group, 44 identified that correctly, whereas, from the 50 individuals in the output control group, 47 identified that membership correctly ($\chi^2 = 71.03$, $p < 0.001$). Furthermore, participants reported high experienced realism ($M = 4.10$, SD = 0.80; on a scale ranging from 1 = very unrealistic to 5 = very realistic) for the scenarios without significant differences between the four different scenarios $F(3,97) = 1.6$, $p = 0.20$, $\eta^2 = .05$. In open-ended responses no concerns regarding the immersion of the scenarios emerged.

3.2.5. Measures

3.2.5.1. Intention to accept the job offer. We adopted Gonzalez et al.'s (2022) measure: "Based only on the description of the organization and its people management, how likely would you accept an offer from InsureX?". Participants responded using a slider measure ranging from 0="extremely unlikely" to 100="extremely likely".

3.2.5.2. Trust in employees. We measured perceived trust in employees with a validated single-item measure[2] from Searle et al. (2011), which we adapted to reflect to what extent individuals thought that the organization trusted their employees ("Overall, to what extent do you think that the organization trusts its employees? "). We used a 7-point Likert scale ranging from 1="to a very low degree" to 7="to a very high degree".

3.2.5.3. Lay beliefs about AI. We measured lay beliefs about AI using a 10-item scale adapted from Von Walter et al. (2022). This scale allows us to tap into existing beliefs individuals have about AI and automation, specifically from a cognitive point of view, which matches our study approach. It asked participants to evaluate different abilities using the question: "What can AI do better than human intelligence?" One example item was: "AI has a high ability to learn". We used a five-point Likert scale ranging from 1="strongly disagree" to 5="strongly agree"). After analyzing the scale statistics and performing an exploratory factor analysis, we deleted two items to improve the internal consistency of the scale and support the single-factor model of the scale. The final scale consisted of eight items ($\alpha = 0.71$).

3.2.5.4. Exploratory measures. In order to better understand the signaling effects of algorithmic control and to understand participants' motives for a choice for or against such control, we asked participants to decide between two job offers at the end of the study. The reference organization was InsureX, whereas the new offer originated from an organization called UnitedSecure which detailed a degree of algorithmic control that was at the opposite end of the spectrum of algorithmic control than the scenario participants had previously read about InsureX. Then, we asked participants to explain their choice using an open-text field.

3.2.5.5. Demographics. We asked participants to indicate their age, gender, education, and employment sector.

3.3. Results

Table 2 provides an overview of all correlations of the variables in Study 1 while Table 3 provides the means and standard deviations of intention to accept the job offer and perceived trust in employees per experimental condition. Table 2 shows that while gender and age did not play a role in our outcome, covariate, and mediator variables, the level of education did. This also reflects the findings of a recent systematic literature review that concluded that level of education has a negative relationship with algorithm aversion (Mahmud et al., 2022). Therefore, we included education as a control variable for all further analyses.

3.3.1. Manipulation checks

In accordance with findings of our pre-test, for all three questions on the degree of algorithmic control, the majority of individuals correctly identify who or what was in charge of monitoring ($\chi^2 = 298.54$, $p < 0.001$), evaluation & feedback ($\chi^2 = 250.31$, $p < 0.001$), and rewarding or sanctioning ($\chi^2 = 320.40$, $p < 0.001$). As for the target of control, 181 out of the 195

Table 2. Means, standard deviations, and correlations of all variables for Study 1.

	M	SD	1	2	3	4	5	6	7	8
1. Degree of alg. control	–	–	1	.00	−0.13**	−0.07	−0.02	−0.03	−0.11*	.05
2. Target of control	–	–		1	.17**	−0.25**	.05	.14*	−0.06	.03
3. Intention job acceptance	54.50	25.20			1	.75**	.18**	.02	.02	−0.14**
4. Trust in employees	3.35	1.10				1	.16**	.00	−0.00	−0.16*
5. Lay beliefs AI	3.50	0.50					1	−0.09	.03	.04
6. Gender	–	–						1	−0.18**	.10*
7. Age	39.11	11.41							1	−0.14**
8. Education	–	–								1

Note. $N = 402$.
*$p < 0.05$.
**$p < 0.01$.

Table 3. Means and standard deviations of intention to accept a job offer and perceived trust in employees per experimental condition for Study 1.

		Intention Job Acceptance Study 1		Trust in employees Study 1	
		M	SD	*M*	SD
Degree of algorithmic control	Non-algorithmic control	57.55_a	25.77	3.32_a	1.44
	Low augmentation	59.20_a	23.15	3.52_b	1.41
	High augmentation	49.88_b	26.00	2.95_b	1.40
	Full algorithmic control	50.82_b	25.17	3.11_b	1.49
Target of control: Behavior		49.91_c	26.99	2.83_c	1.45
Target of control: Output		58.74_d	22.79	3.57_c	1.35

Note. Means in a column that do not share subscripts differ significantly at $p < 0.05$, as indicated by LSD comparisons.

individuals in the behavioral control group identified that correctly, whereas out of the 207 individuals in the output control group, 199 identified that correctly (χ^2=318.96, $p < 0.001$).

3.3.2. Hypothesis tests

3.3.2.1. Moderation analysis. Results showed no main effects of the degree of algorithmic control on our hypothesized mediator (perceived trust in employees; all 95% CIs included 0). However, in line with Hypothesis 1, we found significant interactions of high augmentation with lay beliefs about AI ($b = 0.82$, $SE = 0.36$, 95%CI[0.11,1.52]) and full algorithmic control with lay beliefs about AI ($b = 0.72$, $SE = 0.35$, 95%CI[0.03, 1.4]) on perceived trust in employees. The simple slopes were significant at −1 SD below the mean for high augmentation (b=-0.75, $SE = 0.27$, 95%CI [-1.27,-0.22]) and marginally significant for full algorithmic control (b=-0.51, $SE = 0.28$, 95% CI[-1.05,0.03] $p = 0.0661$) (see Figure 2).

3.3.2.2. Moderated mediation. To test the moderated mediation (Hypothesis 2), we used the Process macro in SPSS. Due to the multi-categorical nature of our independent variable (degree of algorithmic control), we used indicator coding. Non-algorithmic control was coded as the reference category. We used Model 7

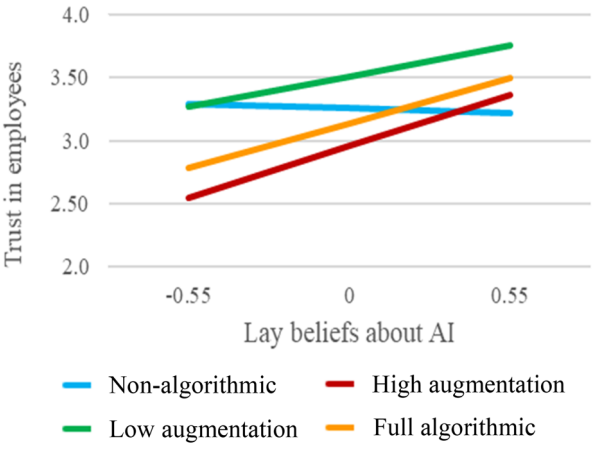


Figure 2. Interaction effect of the degree of algorithmic control and low (−1SD) vs. high (+1SD) levels of lay beliefs about AI on perceived trust in employees (Study 1).

with 5,000 bootstrap samples. We kept the target of control and education as control variables. As hypothesized, perceived trust in employees significantly and positively predicted individuals' intention to accept the offer ($b = 12.71$, $SE = 0.62$, 95% CI[11.49,13.93]). The overall moderated mediation effects were insignificant for low augmentation (*coefficient* = 6.69, $SE = 5.10$, 95%CI[-3.40,16.68]), significant for high augmentation (*coefficient* = 10.70, $SE = 4.78$, 95%CI[1.96,20.51]) and significant for full algorithmic control (*coefficient* = 9.49, $SE = 4.74$, 95%CI[0.38,18.92]), supporting hypothesis 2 (see Table A in supplementary materials for full models results). Additionally, multicollinearity diagnostics indicated no concern, with all VIF values below 2.59. According to Hair et al. (2010), values below 5 indicate low multicollinearity.

3.3.3. Exploratory analysis

3.3.3.1. Target of control. We conducted an ANOVA to explore the effects of the target of control on perceived trust in employees. Results showed that behavioral control ($M = 2.83$, $SD = 1.45$) leads to lower perceived trust in employees than output control ($M = 3.57$, SD;=1.35, $F(3,402)=27.70$, $p < 0.001$, $\eta^2=0.06$), which is in line with the organizational control literature (Cardinal et al., 2017). However, we did not find an interaction effect for the degree of algorithmic control and target of control ($F(3,402)=1.44$, $p = 0.23$, $\eta^2=0.01$).

3.3.3.2. Open-text answers. To analyze participants' open text answers to explain their choice for the first or the second job offer[3], we performed thematic analysis (TA) of all 402 answers. Our TA was mostly inductive (following Braun & Clarke, 2006), but partly guided by our theoretical conceptualization of algorithmic control signals and receiver characteristics. To account for individuals' existing AI beliefs, we categorized individuals'

Table 4. Overview of themes from thematic analysis in Study 1.

Choice human control		Choice algorithmic control	
Preference human	Non-preference algorithm	Preference algorithm	Non-preference human
Personal connection, Human touch	Excessive Monitoring, Distrust, Big Brother	Fairness	Non-dependent on relationship with manager
Nuance, Flexibility	Dehumanizing, Instrumental	Unbiased, Objective	Possible favoritism of manager
Room for negotiation, Voice	Strictness, High pressure	Consistency	The manager has too much power
Valued as a person	Black & White	Innovation	Emotionality humans
Empathy, Warm	Cold	Clear expectations	Micromanaging manager

answers based on their choice into two broad categories. Within those two categories, we then identified patterns and themes and matched them to the reference individuals used (e.g., did they choose human control for its characteristics or because they disliked the algorithm; see Table 4 for an overview).

The first category *choice for human control* has two sublevels: 1a) preference for human control and 1b) non-preference algorithmic control. Individuals who chose human control do so because they want a supportive organization that values individuals and provides voice opportunities, nuance, and empathy. One example was, *"I feel United Secure is more of a people company and personal, Insure X feels very robotic and cold to me"*. On the other hand, individuals with that choice want to avoid an organization where they are monitored too tightly and where algorithms track their every step, which is then perceived as distrusting employees, dehumanizing, and cold, for example: *"Personally I don't like to be overly monitored at all as I deem it a lack of trust…"*

The second category, *choice for algorithmic control*, has the sub-levels 2a) preference for algorithmic control and 2b) non-preference for human control. Individuals who chose algorithmic control do so because they believe that the management procedures are fairer, unbiased, and more consistent. For example: *"The automated system would have set parameters to measure performance. It would be set so that it would be the same for everyone. This seems to be a fairer way of evaluation that should satisfy everyone"*. Others do so because they believe managers have too much power in an organization with only human control, and employees would be too dependent on the relationship with the manager, which could lead to favoritism. For example: *"I believe that management decisions at InsureX could be influenced by personal or subjective opinion of the human manager and therefore open to abuse. While management decisions made by the automated system at UnitedSecure is purely rules-based and therefore not tainted by the possibility of human prejudice."* Our analysis shows that procedural justice plays an important role for individuals, both for those who are averse to algorithmic control and those who

welcome it. Different facets of procedural justice seem to be important, such that voice and morality are emphasized by those opposing algorithmic control and accuracy, and preventing bias by those embracing algorithmic control.

3.3.4. Summary, discussion, and theory development

In Study 1, we found evidence for the moderating role of lay beliefs about AI in the indirect relationship of the degree of control with intention to accept the job offer through individuals' interpretation of how much the organization trusts its employees. For higher degrees of algorithmic control (high augmentation and full algorithmic control), individuals who are more skeptical about AI are less likely to perceive the organization to trust its employees than individuals who are more positive about AI.

The TA of participants' comments revealed reasons why individuals chose for or against the described organization. Individuals who chose human control prefer organizations where individuals are cared for and their voice matters, and they want to avoid close monitoring at work through algorithms, which is interpreted as a distrust signal. Individuals who chose algorithmic control mainly did so because they value organizations with procedures that prevent bias and focus on accurate evaluations. While the themes aligned with our quantitative results regarding perceived trust in employees, they also suggest that individuals are influenced by their impression of procedural justice of organizational control practices.

Procedural justice, which refers to fairness in decision-making and resource-allocating processes (Colquitt et al., 2001), has been a core research focus of the algorithmic control and HRM literature. Most results indicate that algorithmic HR decisions are perceived as more unfair than human HR decisions (i.e., Lee, 2018; Newman et al., 2020). However, some studies also find that (partially) automating HR decisions can be perceived positively (Nagtegaal, 2021). While that may seem contradictory, Langer and Landers (2021) point to the critical notion that procedural justice can be interpreted in two ways that is, in terms of voice opportunities or as bias and consistency. Colquitt's (2001) scale reflects those two different foci as items refer to voice opportunities and morality as well as accuracy, bias, and consistency. Our TA results suggest that the most valued justice aspects also relate to a preference for human or algorithmic control. Thus, algorithmic control may signal different manifestations of procedural justice to different individuals based on existing beliefs about AI. Voice opportunities were emphasized by individuals who chose human control, whereas accuracy and bias were emphasized by individuals who chose algorithmic control. Consequently,

we argue that the two sub-facets of procedural justice act as parallel signaling mechanisms linking the degree of algorithmic control with the intention to accept the job offer.

Hypothesis 3 a: *The more positive individuals are about AI (vs. skeptical), the more likely they will interpret higher degrees of algorithmic control as a signal of procedural justice (bias & consistency) at the organization, which predicts their intention to accept the job offer.*

Hypothesis 3 b*: The more skeptical individuals are about AI (vs. positive), the less likely they will interpret higher degrees of algorithmic control as a signal of procedural justice (voice & morality) at the organization, which predicts their intention to accept the job offer.*

4. Study 2

4.1. Method

4.1.1. Design and sample

As in Study 1, we used a 4 (degree of algorithmic control) x 2(target of control) between-subjects design. We again recruited our sample *via* Prolific with the same filters as in Study 1 (UK, full-time working, native English speakers). We added a filter to exclude participants who were part of Study 1. Our initial sample had 477 individuals. After excluding participants based on attention checks or not finishing the survey, we had N_{final}=440 participants, 223 individuals identifying as males (50.7%), 216 as females (49.1%), and one as non-binary (0.02%). Participant age ranged from 19-70, with a mean of 40.55 (*SD* = 11.80). 30.9% attended secondary education, 42.5% had a bachelor, 23.9% a master's degree, and 2% a Ph.D.

4.1.2. Materials and procedure

We used the same experimental materials and procedure as in Study 1.

4.1.3. Measures

We used the same measures from Study 1 for intention to accept the job offer, perceived trust in employees, and lay beliefs about AI (8 items, α = 0.81). We added the following measures:

4.1.3.1. Procedural justice. We used Colquitt et al.'s (2001) seven-item procedural justice scale. We adapted the items such that they referred to the management procedures at InsureX in the introduction. One exemplary item is: "Please indicate to what extent you think that the management procedures are free of bias?". Answers were rated on a 5-point Likert scale ranging from 1="not at all" to 5="extremely" (α = 0.83). We used MPlus software to perform a confirmatory factor analysis and compared our hypothesized two-factor to

the one-factor model. To assess model fit, we relied on χ^2 and model fit criteria suggested by Kline, (2016): Comparative Fit Index (CFI; good fit:≥0.95; acceptable fit:≥0.90), Standardized Root Mean Square (SRMR; good fit ≤ 0.08; acceptable fit:≤0.10), and Root Mean Square Error of Approximation (RMSEA; good fit ≤ 0.06; acceptable fit:≤0.10). We expected that one factor is centered around voice opportunities and morality, and the other around bias and consistency. Results showed that the fit indices were significantly better ($\Delta\chi2 = 140.95$, $\Delta df = 1$, $p < 0.001$) for the two-factor model ($\chi2(440)=75.85$, RMSEA = 0.10, CFI = 0.94, SRMR =0.06), than the one-factor model ($\chi2(440)=216.80$, RMSEA = 0.18, CFI = 0.82, SRMR = 0.09). Thus, items 1(voice), 2(influence), 6(appeal), and 7(morality) loaded on factor one that we call "voice and morality" ($\alpha = 0.83$). Items 3(consistency), 4(accuracy), and 5 (bias) loaded on factor 2 that we call "bias and consistency" ($\alpha = 0.74$). (See table B in supplementary materials for factor loadings)

4.1.3.2. Demographics. We measured age, gender, education, and employment sector.

4.2. Results

4.2.1. Hypothesis tests

See Table 5 for correlations of all variables for Study 2 and Table 6 for all means and standard deviations, as well as significant mean differences based on LSD comparisons.

To test our model, we ran a parallel moderated mediation model in Process (Model 7) with the degree of algorithmic control as a predictor, lay beliefs about AI as a moderator, and intention to accept the job offer as an outcome. As in Study 1, we added the target of control and

Table 5. Means, standard deviations, and correlations of all variables in Study 2.

	M	SD	1	2	3	4	5	6	7	8	9
1. Degree of alg. control	–	–	1	.00	−0.16**	−0.09	−0.11*	−0.10*	.02	.04	.01
2. Target of control	–	–		1	.12*	.18*	.06	.10*	−0.03	−0.05	−0.04
3. Intention job acceptance	54.64	24.90			1	.63**	.59**	.15**	.02	.04	−0.13**
4. Trust in employees	3.45	1.30				1	.58**	.11**	.00	−0.00	−0.14**
5. Procedural justice	2.83	.72					1	.22**	.02	.09	−0.17*
6. Lay beliefs AI	3.75	0.67						1	−0.11*	−0.03	−0.01
7. Gender	1.5	.5							1	−0.09	.23**
8. Age	40.55	11.80								1	−0.18**
9. Education	–	–									1

Note. $N = 402$.
*$p < 0.05$,.
**$p < 0.01$.

Table 6. Means and standard deviations of intention to accept, perceived trust in employees, and procedural justice per experimental condition for Study 2.

		Intention Job Acceptance		Trust in employees		Procedural Justice (V&M)		Procedural Justice (C&B)	
		M	SD	*M*	SD	*M*	SD	*M*	SD
Degree of algorithmic control	Non-algorithmic control	59.83_{a}	22.84	3.65_{a}	1.30	2.77_{a}	.85	3.19_{a}	.76
	Low augmentation	56.86_{a}	23.73	3.45_{a}	1.34	2.59_{b}	.83	3.29_{a}	.81
	High augmentation	$52.74_{a,b}$	26.94	3.38_{a}	1.30	2.35_{b}	.85	3.15_{a}	.81
	Full algorithmic control	49.19_{b}	25.00	3.35_{a}	1.30	2.38_{b}	.78	3.29_{a}	.81
Target of control: Behavior		51.59_{c}	24.03	3.20_{c}	1.38	2.48_{c}	.85	3.18_{c}	.83
Target of control: Output		57.42_{d}	24.90	3.68_{d}	1.28	2.57_{c}	.83	3.28_{c}	.82

Note. Procedural justice (V&M) refers to the subscale of voice and morality, whereas procedural justice (C&B) refers to the subscale of bias and consistency. Means in a column that do not share subscripts differ significantly at $p < 0.05$, as indicated by LSD comparisons.

education as covariates. The parallel mediators were the organizational values: perceived trust in employees and procedural justice (two subscales), which all significantly and positively predicted intention to accept the offer (all $p < 0.01$). The index of moderated mediation for perceived trust in employees was significant at the high augmentation level (coefficient = 4.28, SE = 2.34, 95%CI[0.12,9.31]). The slopes were significant at -1SD (95%CI [-8.28,-0.66]). For the procedural justice subscale (bias & consistency), the indices for moderated mediation were significant at the high augmentation (coefficient = 1.38, SE = 0.86, 95%CI[0.10,3.45]) and the full algorithmic control level (coefficient = 1.49, SE = 0.90, 95%CI[0.05,3.57]). Figures 3 and 4 depict the simple slopes of perceived trust in employees and procedural justice (bias & consistency)

We found significant negative main effects of high augmentation and full algorithmic control on procedural justice (voice and morality; $p < 0.01$), but we did not find significant interaction effects and, thus, no moderated mediation effects for procedural justice (voice and morality). See Table C in the supplementary materials for an overview of all effects. Also, in Study 2 all VIF values were below 1.58 and therewith indicated no concern regarding multicollinearity (Hair et al., 2010).

To conclude, in Study 2, we found partial support for Hypothesis 1 and Hypothesis 2 (perceived trust in employees), full support for Hypothesis 3a (procedural justice: bias and consistency), and no support for Hypothesis 3b (procedural justice: voice and morality).

5. Discussion

The present research applied signaling theory (Spence, 1973) to explore how prospective job applicants interpret algorithmic control as a signal of organizational values. Our two studies showed that lay beliefs about AI indeed play a critical role in whether higher algorithmic control

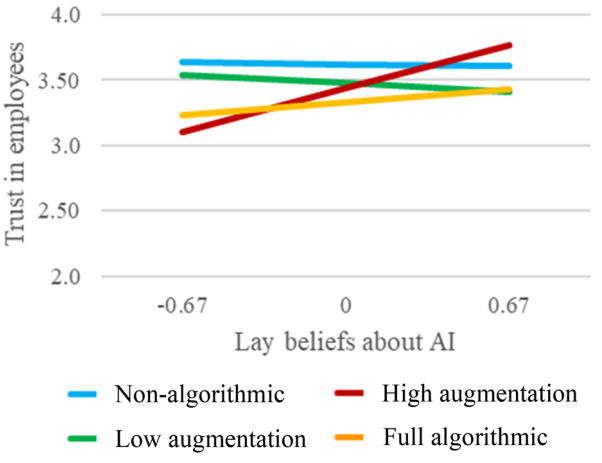


Figure 3. Interaction effect of the degree of algorithmic control and low (−1SD) vs. high (+1SD) levels of lay beliefs about AI on perceived trust in employees (Study 2).

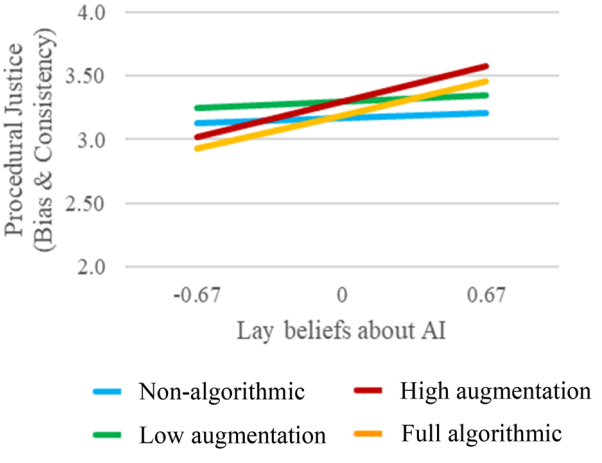


Figure 4. Interaction effect of the degree of algorithmic control and low (−1SD) vs. high (+1SD) levels of lay beliefs about AI on the procedural justice subscale of bias and consistency (Study 2).

degrees (vs. non-algorithmic control) are perceived as a positive or as a negative signal. Algorithmic control signals are not interpreted uniformly; rather, they interact with and are dependent upon pre-existing beliefs about AI. We found that the effect of the high augmentation (Studies 1&2) and full algorithmic control (Study 1) on the value of trust in employees was moderated by individuals' lay beliefs about AI. Individuals who were skeptical about AI were more likely to interpret higher degrees of algorithmic control as a signal that the organization does not trust its employees, compared to those with a more positive view on AI. In Study 2, we found interaction effects of the degree of algorithmic control and lay beliefs about AI on the procedural justice subscale of bias and consistency. This finding, consistent with our Study 1 qualitative results,

indicates that for individuals who are more positive about AI, higher degrees of algorithmic control can serve as a signal of procedural justice, as they believe it can increase consistency and mitigate bias.

Furthermore, perceived trust in employees and procedural justice (bias and consistency) acted as mediators linking the moderated effect of higher control degrees and lay beliefs about AI to the intention to accept a job offer. For procedural justice (voice and morality), we did not find a moderation but strong main effects for higher algorithmic control degrees. This suggests that providing voice opportunities to employees is more likely to be interpreted homogeneously and separate from pre-existing beliefs about AI than perceived trust in employees or procedural justice (bias and consistency), where lay beliefs about AI appear to shape the heterogeneous interpretation of algorithmic control signals.

Regarding the signaling pattern of the four algorithmic control levels (control automation increased with each level), we do not observe a steady increase in our results that mirrors our experimental manipulation. To the contrary, both in Studies 1 and 2, the low augmentation condition is interpreted similarly to the non-algorithmic condition. Thus, some algorithmic support for control is generally perceived as positive. The high augmentation level is interpreted more similarly to the full algorithmic control level, and the effects there depend more on individual preconceptions.

Overall, our findings suggest that organizations need to consider the pre-existing beliefs of their applicants when deploying AI-driven control systems. Misalignment between an applicant's beliefs and the organization's use of algorithmic control could influence their perceptions of trust and fairness, potentially affecting recruitment outcomes. While the general idea that attitudes influence signal interpretation is well-known, our study contributes by exploring how these attitudes specifically shape applicants' perceptions of organizations that employ algorithmic control, an area that has not been systematically examined before.

5.1. Theoretical implications

We make several contributions to the literature. First, we address a question that has not received much attention in research on algorithmic control: to what extent does algorithmic control in HRM create different kinds of signaling effects for different receiver groups outside of the organization? Our results suggest that automated or augmented control functions form an unintentional signal to potential job applicants, even if they are not directly in contact with the practice (yet). This aligns with the HR literature, where HR practices such as training or compensation have been construed as signals from the organizations to employees (Suazo et al., 2009), as well as with the (albeit limited) available research

on unintended signaling effects of HR practices (Dover et al., 2020). Furthermore, we extend previous research on control interpretations by integrating it with signaling theory (Connelly et al., 2011; Spence, 1973). Thus, we construe the signaling effect of algorithmic control as a function of configuration (sender) and individuals' lay beliefs about AI (receiver). By accounting for individuals' underlying beliefs about AI, we paint a more nuanced picture that goes beyond the idea that algorithmic control is always perceived as purely coercive and indicative of distrust (Kellogg et al., 2020).

More specifically, we show that receiver characteristics, in this case, individuals' existing beliefs about AI play a crucial role in interpreting signals such that for individuals who are skeptical about AI, higher degrees of algorithmic control may be perceived negatively, whereas those who are more positive about AI perceive it as a positive signal. Thereby, we turn the focus to the receiver in examining control configurations' signaling effects, which provides interesting avenues for future research. Our findings thereby integrate the divergent perspectives within the algorithmic control literature, which highlight either algorithmic aversion (Mahmud et al., 2022) or algorithmic appreciation (Logg et al., 2019). Specifically, our research indicates that pre-existing beliefs about AI capabilities can influence whether and for whom algorithmic control acts as a positive or negative signal

In addition, we extend previous literature that focused mostly on extreme configurations of algorithmic control (no vs. full algorithmic control) and show that differentiating multiple control configurations ranging from no algorithmic control through low and high augmentation to fully automated control can be insightful. More specifically, we suggest that individual characteristics may not be equally important for all algorithmic control configurations, as our findings suggest that only the interpretation of higher augmentation and full algorithmic control signals depends upon the receiver's characteristics. Low augmentation is interpreted similarly to the non-algorithmic condition. This pattern suggests a tipping point in the augmentation conditions that determines whether it is perceived as more similar to non-algorithmic control or more similar to full algorithmic control, which can be an exciting avenue for future research. Our findings extend previous studies that find augmentation can be perceived similarly or even more positively than no automation (Nagtegaal, 2021; Newman et al., 2020) by suggesting that it is valuable to differentiate further within augmentation degrees.

We also extend the literature on algorithmic control and procedural justice. Our findings from the qualitative part of Study 1 indicate that procedural justice is interpreted differently depending on whether individuals have a preference for or against algorithmic control. Individuals who were

enthusiastic about algorithmic control were so because of expectations of efficiency, consistency, and reduction of bias, whereas those who were more negative about AI were so because of a need for voice and morality of behavior. Therefore, we differentiated between the two factors of procedural justice, which was validated in our quantitative results in Study 2. This contributes to reconciling conflicting results about whether algorithmic control is perceived as a signal of procedural justice or as the exact opposite (Langer & Landers, 2021). Our research suggests that the concept of fairness in decision-making can have multiple interpretations, as it holds different meanings for different individuals. Consequently, we recommend that future studies separately examine these two factors of procedural justice to gain a more nuanced understanding.

Our study also extends signaling theory (Connelly et al., 2011) by detailing that signal interpretation depends upon the signaling mechanism under scrutiny, such that for some values, the interpretation is prone to be influenced by the receiver's individual beliefs. In our study, we show that for perceived trust in employees and the procedural justice bias and consistency facet, interpretations are more heterogeneous due to differences in individuals' lay beliefs about AI that shape algorithmic control interpretation. Whereas for the procedural justice voice and morality facet, algorithmic control is interpreted more homogeneously, independent of individuals' lay beliefs. To what extent individuals' lay beliefs play a role in signaling related to other organizational values forms an interesting avenue for future research.

5.2. Practical implications for HRM

Our research provides practitioners with a better understanding of algorithmic control signals. As organizations increasingly deploy algorithms to automate or augment control functions in HR, it is crucial to consider not only the reception of algorithmic control by current employees but also its impact on potential employees. An organization's preferences regarding algorithmic control have reputation effects beyond the organization, particularly among prospective applicants, and organizations with superior reputations tend to attract stronger talent (Eccles et al., 2007). We show that the decision to augment or automate organizational control functions in HRM can send an unintentional signal to potential employees about organizational values. Our research suggests that even if individuals have not (yet) had direct contact with control practices, they use information about algorithmic control in HRM jointly with their own underlying beliefs to infer organizational values. In turn these values guide their decision to accept or reject a job offer from the organization.

Organizations could consider proactively shaping the signals they want to send to potential applicants. We propose a couple of practical measures that organizations could implement: First, we suggest communicating transparently about algorithmic control practices and theiri purpose in HRM to current and prospective employees. Second, we suggest to provide detailed explanations about how these practices enhance the fairness of decision-making processes at the organization. Third, organizations should proactively monitor how algorithmic control impacts the organization's reputation, for example, through monitoring word of mouth on social media or employer review platforms. Thereby, organizations can proactively manage any negative perceptions or misinformation.

In addition, realizing that algorithmic control can send mixed signals is essential. Depending on the audience, organizations can use algorithmic control signaling qualities to attract the "right" applicants. If organizations understand the characteristics of their target applicant group, they can use the differential interpretation of algorithmic control to their benefit, such that organizations that want to attract individuals who are excited by automation may adapt their communication strategy to framing algorithmic control as a procedural justice signal (increasing evaluations' consistency and accuracy of evaluations and omitting human biases). For example, organizations that know their target population values trust, voice, and personal relationships may have to adapt their communication about algorithmic control to signal the purpose behind algorithmic control (i.e., developmental), leading to more positive perceptions. More directly communicating about organizational values might help avoid misinterpretation of control signals.

5.3. Limitations and future directions

It is important to address some limitations to our findings. First, we used hypothetical scenario studies to test our model. This approach can be valuable because it allowed us to investigate relationships between constructs in a controlled manner (Atzmüller & Steiner, 2010). However, the hypothetical nature of vignette studies limits external validity. Participants' responses may not fully capture the complexity of real-world behavior, as actual job search settings involve a variety of contextual factors, social dynamics, and emotional responses that are challenging to replicate in experimental vignette studies. Yet, in line with recommendations for using experimental scenarios in management science (Aguinis & Bradley, 2014), we chose this methodology intentionally because it allowed us to focus on the cognitive interpretation of algorithmic control and introduce a

much-needed level of nuance to algorithmic control configurations. To enhance the ecological validity of our findings, future research could enrich our results through field studies or experiments with active job seekers. Such approaches could provide insights into the relative importance of algorithmic control's signaling effect in the search process.

Second, we defined four degrees of algorithmic control. However, our results still contained inconsistencies concerning the augmentation and full algorithmic control conditions. This might point toward the need for even more granularity in operationalizing the degrees of algorithmic control. Future research may look at other algorithmic control configurations and pay even more detailed attention to operationalizing augmentation conditions, which could uncover a tipping point and describe this relationship in a curvilinear way.

Considering future research, it could be interesting to investigate how lay beliefs about AI develop over time and are affected by actually being in contact with algorithmic control. Future studies could, for example, explore job seekers' lay beliefs prior to employment and reassess them after having been exposed to algorithmic control for an extended period of time. An interesting question could be whether lay beliefs about AI are reinforced or discarded after becoming more acquainted with the technology in organizational practice.

Also, communication about algorithmic control is an exciting avenue. For example, how can organizations shape their official communication about algorithmic control, and how does this affect inferred organizational values? Furthermore, how does official communication by the organization interact with word of mouth about algorithmic control practices? Taj (2016) highlights that the signal order may influence signal perception. Thus, exploring how different types of algorithmic control signals can interact with one another and how this affects the organization's credibility and attractiveness might be worthwhile.

6. Conclusion

We investigated how algorithmic control can elicit mixed signals amongst potential applicants based on their pre-existing beliefs about AI. Our results show that algorithmic control can be interpreted as either a positive or a negative signal of an organization's values and consequently affect applicants' intention to accept a job offer. This research advances signaling theory (Connelly et al., 2011) and research on algorithmic control by demonstrating that the strategic decisions organizations make in using algorithmic control can be to their advantage or disadvantage, depending on whom organizations are looking to attract as applicants.

Notes

1. To explore whether the target of control plays a relevant role in our hypothesized relationships, we exploratively included it in our design to account for potential effects. For our hypothesis testing, we included the target of control in all our analytical models as a control variable to exclude any substantial influences.
2. A recent study by Matthews et al. (2022) underlines the lack of evidence that only conceptually narrow constructs can reliably and validly be measured with single item measures and suggests the appropriateness of using validated single-item scales.
3. Results of the Chi-Square test revealed that participants who were in the human control condition also preferred that condition (65 individuals) over the algorithmic condition (38). Individuals who were in high augmentation condition, preferred the human control offer 87 (vs. 13), which was presented to them as the second offer. In the full algorithmic control condition 81 (vs. 15) chose the second offer, which described human control. The only exception to that trend was found in the low augmentation condition, where more individuals (82) preferred the algorithmic control offer. All group differences were significant (χ^2=69.29, p<.001). In total, 254 individuals chose the human control offer and 148 chose the algorithmic control offer.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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Data availability statement

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

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