This (AI)n't fair? Employee reactions to artificial intelligence (AI) in career development systems

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ORIGINAL PAPER

This (AI)n't fair? Employee reactions to artificial intelligence (AI) in career development systems

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Abstract

Organizations increasingly implement AI for career development to enhance efficiency. However, there are concerns about employees' acceptance of AI and the literature on employee acceptance of AI is still in its infancy. To address this research gap, integrating justice theory, we investigate the effects of the deciding entity (human, human and AI, and AI) and the impact of the data source (internal data, external data), on employees' reactions. Using a scenario-based between-subject design, displaying a common situation in organizations ($N = 280$) and an additional causal-chain-approach ($N = 157$), we examined whether a decrease of human involvement in decision making diminishes employees' perceived fairness and satisfaction with the career development process and increases their perceived privacy intrusion. Although we also considered other data sources to moderate the proposed relationships, we found no support for interaction effects. Finally, fairness and privacy intrusion mediated the influence of the deciding entity and data source on turnover intention and employer attractiveness, while satisfaction with the process did not. By addressing how the employees react to AI in career development–showing the negative reactions, our study holds considerable relevance for research and practice.

Keywords Artificial intelligence · Employees' reactions · Fairness · Organizational attractiveness · Privacy intrusion · Turnover intentions

JEL Classification O15 · C99 · M10

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1 Introduction

Recent developments of algorithms and *artificial intelligence*[1] (henceforth: AI) have become widespread among human resource (HR) functions due to their presumed efficiency-increasing effect on HR processes and practices (Prikshat et al. 2023) it can be especially helpful with regard to data analysis and classification (Burger et al. 2023). Stored in HR information systems or cloud systems, AI is able to use and analyze data about for example hires, personal characteristics, hours worked, and various performance-related measures of employees (Leicht-Deobald et al. 2019; Wirges and Neyer 2023), which are important predictors for career development and career success (Ng et al. 2005). In this regard, AI can use data from internal and external sources (Angrave et al. 2016; Karim et al. 2015; Kellogg et al. 2020; Oswald et al. 2020) to predict certain key HR outcomes (Angrave et al. 2016; Leicht-Deobald et al. 2019; Robert et al. 2020). Hence, AI is able to either support humans in their decision-making (i.e., augmentation; Langer and Landers 2021) or replace humans by automating decision-making (i.e., automation; Langer and Landers 2021, Wesche et al. 2024).

Concerning the data source, AI is able to analyze employees' digital footprints collected *within* the organization, such as emails, online collaborative tools, and individual output (Angrave et al. 2016), and *outside* the organization, such as social media (e.g., Facebook, LinkedIn, X), posts, blogs, and other websites (Kern et al. 2016; Kosinski et al. 2016; Landers et al. 2016; Oswald et al. 2020; Roth et al. 2016). IBM, Greenhouse, Jobvite, Microsoft, SAP, and Workday already offer various talent management software packages that are able to integrate these mass data about employees from various sources (Angrave et al. 2016; Edwards et al. 2024; Leicht-Deobald et al. 2019; Oswald et al. 2020; Tambe et al. 2019). The software Microsoft 365, for instance, has been criticized for allowing managers to track their employees and productivity (Hern 2020). Further, social media posts and likes of employees have become a new and potentially authentic source of information for organizations (Roth et al. 2016; Tambe et al. 2019). Given these rapid technological developments, there is a need to examine employee reactions towards the different data sources that organizations have begun to explore by using AI for decision-making processes.

While previous research mainly focused on AI acceptance and fairness perceptions of stakeholders outside the organization, especially applicants (e.g., Acikgoz et al. 2020; Hiemstra et al. 2019; Köchling et al. 2023; Langer et al. 2019), knowledge is still scarce about the influence of AI on employee reactions within the organization (Leicht-Deobald et al. 2019; Robert et al. 2020). In this regard, employee reactions and fairness perceptions of AI in the context of career development will become paramount. Career development within an organization, namely

[1] By using the umbrella term 'artificial intelligence' in this study, we follow Langer and Landers (2021) and mean traditional human-programmed algorithms as well as recent developments in the applications of machine learning, deep learning, artificial neural networks, natural language processing, and large language modeling in HR management (see also Prikshat et al. 2023).

performance evaluation, training recommendations, personalized coaching, and promotion to new positions, is the organizational process or intervention of identifying and matching highly skilled and talented employees with organizational needs and strategic positions (Herr 2001; McDonald and Hite 2005). Given that the problems of the so-called 'war for talent' recently shifted towards talent management and talent retention, organizations need to promote their talents and offer beneficial career paths to retain them because these talents perform better in their positions than other equally motivated individuals (Angrave et al. 2016; Chamorro-Premuzic et al. 2016).

To understand the impact of AI on individuals, previous research utilized organizational justice theory (Bies and Moag 1986; Colquitt 2001; Colquitt et al. 2001; Greenberg 1993) and mainly focused on the influence of AI on distributive and procedural fairness (see Table 3 in Robert et al. 2020). However, interactional fairness perceptions of AI found less attention (Karim et al. 2015; Robert et al. 2020) despite their importance for other outcomes, such as collective esteem (Colquitt 2001), leader-member-exchange (Roch and Shanock 2006), and task performance (Alder and Ambrose 2005). While the majority of research focused on applicants' justice perceptions of AI during recruitment (e.g., Gonzalez et al. 2022; Hunkenschroer and Luetge 2022; Ochmann et al. 2024), there is less evidence of employees' interactional justice perceptions depending on whether a human or an AI system makes decisions during career development and promotions (e.g., Binns et al. 2018; Bankins et al. 2022; Newman et al. 2020). Following (Bies 2001), we argue that interactional justice perceptions, such as fair and respectful treatment as well as privacy intrusion (Cropanzano et al. 2015; Roch and Shanock 2006), need to be considered for a better understanding of employee reactions towards AI usage in a career development context. From a theoretical perspective, privacy intrusion is still an important albeit understudied mechanism for explaining employees' justice perceptions of AI (Hunkenschroer and Luetge 2022). Thus, our primary research questions for this study are: (1) does the deciding entity (AI-supported decision or AI decision without humans) affect employee reactions in terms of interactional justice during promotion situations and career development? (2) does the variety of data sources for a promotion decision diminish or increase these employee reactions? and (3) do these employee reactions mediate the relationships between the deciding entity and organizational attractiveness or turnover intentions?

Consequently, we contribute to the existing literature on organizational justice and acceptance of AI theoretically, empirically, and practically. First, we build and extend the theory by re-introducing privacy intrusion as a vital construct in the context of AI, data, and employee reactions. In doing so, second, we go beyond procedural and interpersonal fairness and empirically test the mediating influence of privacy intrusion in an AI-aided career development process. In addition, we extend existing knowledge about employee reactions toward the deciding entity (i.e., human evaluation, AI-supported evaluation, AI evaluation) and the data source (i.e., only internal data vs. external and internal data) used during the evaluation of the career development process. While procedural fairness is a well-known mediator in connection with AI and individual reactions in HRM (e.g., Hunkenschroer and Luetge 2022; Köchling and Wehner 2020; Robert et al. 2020; Roch and Shanock 2006),

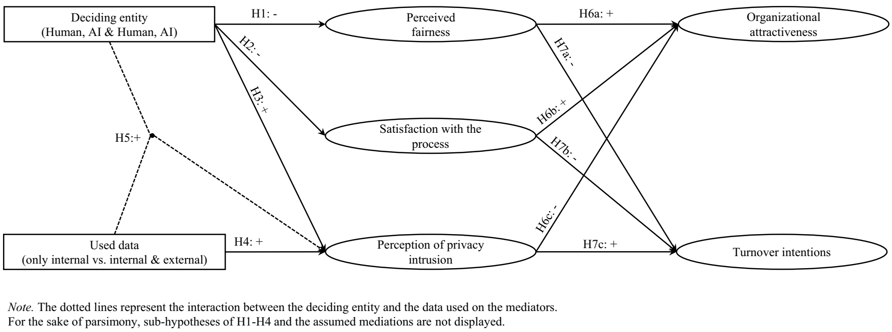


Fig. 1 Representation of the research model

interpersonal fairness (i.e., satisfaction with the career development process) and privacy intrusion may help to better understand employees' adverse reactions towards the use of AI 'within' the organization (Leicht-Deobald et al. 2019, p. 378). Third, our findings have substantial practical implications for managers using AI in career development because we show the potential adverse consequences for the company. Figure 1 depicts our main constructs and relationships that will be hypothesized in the following.

2 Theoretical framework

2.1 AI and organizational justice theory

In the context of HRM, algorithms and AI increasingly make decisions that HR managers have made before or support HR decision-making, which is ought to increase decision quality and efficiency (Langer and Landers 2021; Möhlmann et al. 2021; Prikshat et al. 2023; Zhang and Amos 2024). In this regard, Meijerink and colleagues (2021, p. 2547) defined the term 'algorithmic HRM' as the "use of software algorithms that operate on the basis of digital data to augment HR-related decisions and/or to automate HRM activities. "Traditionally, career decisions about promotions and bonuses are made by HR managers about the employees. More recently, AI supports or even makes decisions about employees concerning their performance evaluations, trainings and coachings, and career development (Malik et al. 2022, 2023; Zhang and Amos 2024), which affects employees' career paths, well-being, and lives–and often without their consent or knowledge (Langer and Landers, 2021).

Organizational justice theory (e.g., Bies and Moag 1986; Colquitt 2001; Colquitt et al. 2022; Cropanzano et al. 2015; Greenberg 1993) allows for hypothesizing employee reactions toward the usage of AI during a decision process for career development. In this regard, organizational justice is more descriptive and subjective than objective reality, and it is, therefore, a personal evaluation of agents' ethical behavior (Cropanzano et al. 2007). Accordingly, individuals examine the justice of an outcome (distributive justice), the appropriateness and justice of a process (procedural justice), and the appropriateness of the treatment the employees received from the deciding entity (interactional justice). Traditionally, interactional justice is further divided into interpersonal justice and informational justice (Colquitt et al. 2001; Cropanzano et al. 2015; Greenberg 1993). Interpersonal justice reflects the degree of politeness, dignity, and respect to which authorities and deciding entities treat individuals during the decision process, while informational justice refers to the degree of providing information and explanations about why certain procedures or processes were applied to achieve fairness (Colquitt et al. 2001; Robert et al. 2020). Systematic reviews and meta-analytic results have shown that the different types of justice are related to individual outcomes, such as trust, commitment, performance, satisfaction, organizational attractiveness, and withdrawal behavior (Chapman et al. 2005; Colquitt et al. 2001, 2022; Hausknecht et al. 2004; Robert et al. 2020).

In this study, we focus on procedural, interpersonal, and informational justice perceptions as important fairness mechanisms for explaining employee reactions toward the deciding entity and the data source during a career development process. While procedural justice has been found considerable attention in previous literature, only a minority of studies focused on interactional justice or the organizational context that surrounds AI systems (Robert et al. 2020). This partially resonates with findings from systematic literature reviews about algorithmic biases and AI-fairness that highlight the importance of examining different justice types within the organizational context, in which AI systems are applied (e.g., Budhwar et al. 2022; Köchling and Wehner 2020; Kordzadeh and Ghasemaghaei 2022).

At first glance, it seems surprising that interpersonal and informational justice perceptions *within* organizations found less consideration in previous AI research. In information system research, a primary concern is the distributive justice of an outcome predicted by AI systems and the procedural justice of a decision-making process supported by AI (Köchling and Wehner 2020; Robert et al. 2020). Nevertheless, within an organization and especially during the career development, we suggest that interpersonal and informational justice perceptions of AI are equally important. Concerning informational justice, it is difficult or even impossible for authorities and executives to explain the reasons for certain results and recommendations by an AI because the trained algorithms and statistical models are a 'black box' (Cheng and Hackett 2021). Of course, executives are able to explain the evaluation criteria and what kind of information will be used to train the AI system to their employees, but they are not able to make the inherent mechanism of the AI systems transparent to them (Wiblen and Marler 2021).

Therefore, in an organizational context where AI is used to analyze internal and external data and support career decisions, privacy intrusion should play an essential role for employee reactions. Privacy intrusion reflects a person's perception of intrusion into the personal information space (Xu et al. 2008). Privacy intrusion violates employees' ethical standards and/or principles of appropriate treatment (Bies 2001; Karim et al. 2015). Using AI for career development decisions will raise concerns about what kind of data is used to train the AI system, how AI predicts an individual's potential, and whether AI is following ethical standards (Köchling and Wehner 2020; Tambe et al. 2019). Robert et al. (2020) also identified the lack of focus on interpersonal and informational justice as well as on the organizational context of an AI system used within organizations, which limits our understanding and prediction of potentially negative employee outcomes.

In summary, we theoretically transfer and empirically examine procedural, interpersonal, and informational justice of employees toward the usage of AI. Besides procedural justice (i.e., fairness), we emphasize the importance of interpersonal justice (i.e., satisfaction with the career development process) and informational justice (i.e., privacy intrusion) from an employee's perspective that deepens the understanding of employees' adverse reactions towards the use of AI within the organizational context of a career development process. In doing so, we follow recent calls for considering different fairness types (Robert et al. 2020; Tambe et al. 2019) and the organizational context in which AI systems are embedded (Leicht-Deobald et al. 2019; Robert et al. 2020).

2.2 AI in the career development context

In general, career development comprises organizational policies and practices to constantly improve employee's knowledge, skills, and abilities, and to achieve career-related goals (Ng et al. 2024). These organizational policies and practices yield into objective and subjective career outcomes; while objective career outcomes usually encompass promotion to new positions and an increase in salary, subjective career outcomes rather include commitment, job satisfaction, turnover intentions, and job performance (Bagdadli and Gianechini 2019; Ghosh and Reio 2013). To inform organizational policies and practices for career development, common HR software systems already collect and store a variety of employee data and incorporate AI for analytics, prediction, and decision-making (Edwards et al. 2024; Prikshat et al. 2023).

The access to employee data and the use of AI for various HR functions has also increased due to shifts in working habits caused by the Covid-19 pandemic (Cheng and Hackett 2021; Corbyn 2022; Köchling and Wehner 2020; Leicht-Deobald et al. 2019; Leonardi 2021). Companies are increasingly using employee monitoring tools, also called "bossware." Some of these tools for example can activate the camera and microphones, take screenshots, and measure mouse activity. These tools help to measure productivity and satisfaction, as well as the risk of job turnover. In addition, a growing number of these tools use AI for analyzing the data (Corbyn 2022; Garr and Jackson 2019). For example, IBM uses an AI-based tool as part of its career planning process that can predict with high accuracy which employees will leave the company in the near future (McGregor 2019). Moreover, Microsoft launched a Productivity Store at the end of 2020, which measures productivity by evaluating the use of various Microsoft apps (e.g., participation in meetings). Due to criticism, Microsoft has adapted the product so that employees cannot be identified (Hern 2020). IBM goes a step further and relies on automated employee feedback instead of annual reviews using a virtual assistant called, which highlights strengths and weaknesses as well as opportunities for improvement (IBM 2022).

In addition, companies also have increasingly different types of data that can be analyzed (Kellogg et al. 2020; Mikalef and Gupta 2021; Shin et al. 2022; Simbeck 2019). Typical data held in HR software systems are composed of information on the employees hired, employee salary, the number of worked hours, and various performance-related measures (Leicht-Deobald et al. 2019). Moreover, electronic surveillance, for example, can easily take place outside the workplace (Mikalef and Gupta 2021), via systems that can scan social media activity or apps that are downloaded on employees' phones to access GPS location data (Bernhardt et al. 2021). Some companies also consider the employee's digital footprints (e.g., professional profiles, such as LinkedIn, and nonprofessional profiles, such as Facebook) (Angrave et al. 2016).

Examples of social media information of interest to HRM include the content of employee or organizational posts or blog content that may be of interest to gain insights into employee attitudes (Oswald et al. 2020). Professional social media sites are a rich source of user data related to knowledge, skills, abilities, and other characteristics (KSAOs) required and desired for various job positions (Oswald et al. 2020). One provider of an AI tool that uses company data and social media data to analyze employee behavior is Veriato. Veriato gives every employee a daily "risk score" indicating the likelihood of posing a security threat by monitoring their remote, hybrid, and in-office environments, such as mail, chat, application use, and web browsing history (Veriato 2023). Another example is Ferretly, which has the ability to run an analysis of public posts, including both text and images of the employees or applicants, identifying prejudices, threats, and disparaging comments to reduce turnover and create a safer environment (Ferretly 2024). The tool Crystal is another example, predicting personality traits such as dominant, influential, and steady based on publicly available traits such as skills, interests, and other information on the profile page (Crystal 2024).

In addition to and based on the nature of the data, the career decision and the career process are highly relevant for employees. The decision and the process of inclusion in a career development program can cause several emotional reactions resulting from the feeling of (in)justice (Tzafrir and Hareli 2009). In the case of a negative decision on career development, employees might take the negative decision personally if their managers are responsible for the decision, which then negatively impacts the rejectee, stimulating feelings of envy, a sense of exclusion, and reduced performance (Deri and Zitek 2017; Schaubroeck and Lam 2004). Moreover, employees might feel less valued if the decision has been handed over to an AI system (Dahm and Dregger 2019; Langer and Landers 2021) because this can give the employees the feeling that the career decision lacks humanity and personal interaction (Bankins et al. 2022; Binns et al. 2018). Finally, if an AI system decides about promotions or bonuses of employees, this is considered to be less trustworthy (e.g., Bankins et al. 2022; Höddinghaus et al. 2021; Wesche et al. 2024) and less fair (e.g., Bankins et al. 2022; Newman et al. 2020) than decisions made by humans. Consequently, dissatisfaction, distrust, and unfairness perceptions can result in lower organizational attractiveness (e.g., Höddinghaus et al. 2021), higher job turnover (e.g., Scott et al. 2017), demotivation and emotional exhaustion (e.g., Edwards et al. 2024).

2.3 Hypothesis development

We formulate hypotheses regarding the deciding entity, which considers the differences between an exclusive human evaluation, human evaluation supported by AI, and an exclusive AI evaluation, as well as the data source, which considers the use of only internal data in comparison to external combined with internal data. Furthermore, we suggest that fairness perceptions, satisfaction with the decision process, and privacy intrusion mediate the influence of the deciding entity on organizational attractiveness and turnover intentions (see also Fig. 1).

Fairness. In career development, it is important to answer the question of how fair employees perceive the decision process for their evaluation and promotion (McDonald Hite 2005; Wiblen and Marler 2021). Even if the process is fairer from a statistical point of view, this does not necessarily mean that employees perceive the process to be fairer; hence, it is about what employees believe to be just (Cropanzano et al. 2015). Especially in career development, where it is about personal growth and development, the employee's perceived fairness and possible adverse reactions play an essential role.

The use of algorithms and AI for evaluations of employees and decisions about their careers within the organization is a double-edged sword. During the promotion of talents and performance evaluations, it is common knowledge that organizations need to avoid or reduce the human bias of their evaluators (Dries 2013; Tambe et al. 2019). On the one hand, AI systems promise to be more rational, less emotional, and less subjective than their human counterparts (Gonzalez et al. 2019; Leyer and Schneider 2021). AI might reduce subjective biases by focusing on numerical criteria and removing those informations that is irrelevant for performance evaluation, such as age, gender, ethnicity, and other demographics (Tambe et al. 2019). Hence, AI decisions and recommendations should be more objective than those made by HR managers who may rate employees with a human bias (Kaibel et al. 2019; Woods et al. 2020). On the other hand, AI and algorithms are vulnerable to several different biases, such as historical, representation, and technical biases, due to their reliance on historical data (Friedman and Nissenbaum 1996; Köchling and Wehner 2020). For example, despite high accuracy, the under-representation of certain groups in the training data, such as gender or ethnicity, may lead to unpredictable outcomes and a replication of inequalities by algorithms (Köchling et al. 2021).

From an employee's perspective, AI also lacks human intuition and the capability to evaluate and judge the social context, which is an essential aspect for procedural fairness perceptions (Lee 2018; Suen et al. 2019). Moreover, organizations often rely on algorithms designed by a third-party technology supplier (e.g., IBM, SAP) to facilitate and standardize their talent management and promotion processes (Angrave et al. 2016; Wiblen and Marler 2021), but without knowing how the algorithms were trained, which input data were used, and how the factors are weighed for prediction. Due to the potential biases of AI and the lack of knowledge and transparency, we assume that the perceived fairness is lower when the AI system makes a decision compared to humans in the career development process. The accuracy and consistency of AI-based decisions are often unknown to the employees; thus, uncertainty about how AI works and how its weighting is achieved suggests that employees are concerned about the appropriateness of the decision process. For example, Lee (2018) showed that individuals rate work evaluations by humans to be fairer than an algorithmic decision because work evaluations require subjective judgment and emotional capabilities. Similarly, decisions made by an AI system are perceived to be less fair than decisions made in a group discussion (Lee and Baykal 2017). Thus, employees might believe that AI lacks human intuition because the AI system makes judgments solely based on numerical data, while being incapable of taking personal and social qualities into account (e.g., leadership skills, intentions, and individual potential in the future) (Lee 2018; Newman et al. 2020).

In a similar vein, a combination of a human and AI evaluation during the career development process should be perceived to be less fair than a human evaluation. Despite the potential benefits of AI to reduce human bias, we assume that the supposed advantages of AI do not outweigh the negative justice perceptions by employees because evaluators might–consciously or unconsciously–heavily rely on the recommendation and ranking by the AI system. Wiblen and Marler (2021) described that the implementation of an algorithmic talent management system constrained the discussions of subjective factors, which cannot be measured objectively. Still, the uncertainty about how AI works and how certain performance data influence the AI recommendation will lead to negative employee reactions concerning the appropriateness of the decision process. Thus, we propose that employees' fairness perception of the process will be lower if an AI system supports the process, even though these negative reactions may be less extreme in comparison to an exclusive AI decision.

H1 The exposure to (a) a combined human and AI evaluation and (b) an exclusive AI evaluation will lead to a more negative evaluation of fairness compared to an exclusive human evaluation.

Satisfaction with the process. Beyond the evaluation of procedural fairness, employees make judgments about interpersonal treatment, which is reflected by their satisfaction with the process. Satisfaction with the process reflects a person's perception of being valued and esteemed during a decision process (e.g., Wehner et al. 2015). Interactional justice involves social sensitivity, dignified treatment, and respectfulness (Colquitt 2001; Cropanzano et al. 2007). Justice literature emphasizes that interpersonal treatment, two-way communication, and the behavior of the HR personnel according to justice rules positively influence individual reactions to selection systems (e.g., Cropanzano et al. 2007; Gilliland 1993, 1994; Leventhal 1980). The career development process belongs to those organizational processes that require human skills because supervisors need to weigh and evaluate subjective factors and the behavior of their subordinates (Glikson and Woolley 2020; Lee 2018). Among other predictors, supervisor support is positively related to career satisfaction because employees need personal and helpful feedback concerning their job and task performance (Ng et al. 2005). However, employees will feel less valued and less supported by their supervisor when AI is used for this decision (Dahm and Dregger 2019). Similarly, trust is higher in human decisions than in algorithmic decisions (Glikson and Woolley 2020; Lee 2018).

We assume that AI support or an exclusive AI evaluation during career development diminishes satisfaction with the process because the inclusion of AI into the process decreases interpersonal treatment and reduces the consideration of individual factors that are not measurable objectively. Lee (2018) showed that work evaluations by an algorithm reduce trust, which induces negative emotions due to the lack of human intuition and empathy. If an AI system makes career development decisions independently from humans, this diminishes support and responsibility by their supervisors (Wiblen and Marler 2021). Moreover, employees will feel less valued and less respected because evaluators and, hence, the organization take less time for each case. Wiblen and Marler (2021), for instance, described that HR managers played only a limited role in talent promotion with an AI system since they used the standardized algorithmic recommendation to defend their decision if employees questioned this decision. Similar to fairness perceptions, the uncertainty about how certain performance data influence the AI recommendation will lead to negative employee reactions concerning satisfaction with the decision process when AI is supporting the evaluation. Thus, we propose that employees' satisfaction with the process will be lower if an AI system supports the process, even though these negative reactions may be less extreme in comparison to an exclusive AI decision.

H2 The exposure to (a) a combined human and AI evaluation and (b) an exclusive AI evaluation will lead to a more negative evaluation of satisfaction with the process compared to an exclusive human evaluation.

Privacy intrusion. Privacy is important for justice in organizations (Bies and Tyler 1993; Stone and Stone-Romero 1998). Hence, for organizations, privacy is a complex issue and of increasing importance for organizations, as companies have growing possibilities of analyzing personal data due to rapid technological innovations in HRM and the availability of excessive internal and external data (Wirges and Neyer 2023; Xu et al. 2008). At the same time, privacy concerns are growing among employees and labor unions due to the increasing analytical methods and data availability (Martin 2019; Tambe et al. 2019). Employees' perception of information privacy can be divided into beliefs about their control over their personal information and the information space. This includes (a) the extent of employees' control over their personal information, its collection, and storage, (b) the extent of their control over how organizations handle the gathered data, and (c) the extent to which the procedures are perceived to be legitimated (Alge et al. 2006). Moreover, privacy intrusion means the incursion into the personal information space, which could create discomfort and harm (Xu et al. 2008). During data collection and training of AI, it may be that the ethical rules cannot be observed and thus employee privacy is invaded (Leventhal 1980; Oswald et al. 2020).

Since AI is a new phenomenon within the career development process, and the basis for these systems is a large amount of data, we expect that the use of AI is not consistent with employees' ethical norms; thus, concerns about privacy intrusion should arise. AI-based decision making can be perceived as a kind of permanent electronic surveillance and control of employees. Due to the perceived organizational control, employees may feel that their privacy is compromised (Alge et al. 2006). McNall and Roch (2007) showed that traditional observation by human supervisors was least invasive into privacy than electronic performance monitoring or surveillance. Consequently, employees might get concerned about their information privacy due to AI because the information that they want to keep hidden or private from others will be available to the organization (Bies 2001). This will be more problematic if employees do not know what kind of data was collected, stored, and analyzed by AI for individual prediction. Similar to fairness perceptions and satisfaction with the process, again, we propose that privacy intrusion will be higher if an AI system supports the process, even though employee reactions may be less extreme in comparison to an exclusive AI decision.

H3 The exposure to (a) a combined human and AI evaluation and (b) an exclusive AI evaluation will lead to a higher perception of privacy intrusion compared to an exclusive human evaluation.

Data source. The use of external data, such as social media (either with professional or nonprofessional profiles), posts, blogs, and other websites (Kern et al. 2016; Kosinski et al. 2016; Landers et al. 2016; Oswald et al. 2020), for HR purposes is often criticized through the lens of ethical and privacy concerns (Stoughton et al. 2015). Humans use the internet, web applications, and social media to connect with others and exchange information, for instance, by sharing pictures, experiences, and personal opinions. Most do not expect that these pieces of information can be used to evaluate job performance (Mgrditchian 2015). Providers such as Jobvite, Veriato, or IBM's Blue Match software analyze social media posts of employees and use this information to score employees and their predict career advancement since this information are considered to be more authentic (Roth et al. 2016; Tambe et al. 2019). Employees could view the use of their social media data, even if it is normally publicly available, as a violation of their privacy (Bauer et al. 2020). Furthermore, it can be assumed that most employees see the use of external data as something negative, as companies are probably looking for the "red flag" in this data (Cook et al. 2020). Additionally, protected personal information that are not directly "job-related", including employees' age, race/ethnicity, religious affiliation, number of children, marital status, and disability may be available (Bauer et al. 2020; Levashina et al. 2017). In the recruiting context, research showed that the screening of social networks in the application process led to a sense of invasion of privacy, resulting in lower organizational attractiveness by applicants (Stoughton et al. 2015). In contrast to hiring situations, work-related internal data about employees are often available, which can be used to judge an employee's potential for a certain career. However, if an employer uses external data in addition to these internal data, this should decrease the perceived appropriateness of using such data for career development decisions. Thus, we hypothesize the following:

H4 Exposure to an evaluation that uses both external and internal data will lead to a higher perception of privacy intrusion compared to an evaluation that uses only internal data.

We also expect that the negative effect of decision making supported by AI or made entirely by AI will be enhanced if external data are included in the decision-making process because humans are concerned about data abuse when using AI and perceive AI-based managerial decisions as less trustworthy (Höddinghaus et al. 2021; Lee 2018). The privacy concerns may be even intensified when the external data is analyzed algorithmically because it is easier to connect data points and create new pieces of information that can harm privacy (Shin et al. 2022; Simbeck 2019). Therefore, the additional increase in velocity, given the potential computational speed of an AI when using big data, could provide employees with the feeling that they have even less control over what kind of data or information is used and how much of their private life is involved in their evaluations. This relates to the nature of such data, which are often produced through complex networks to create sound data of an individual (Sivarajah et al. 2017). Consequently, a human might not be able to process all this information, while an AI will be able to provide these (when interacting with a human) or use these independently (when deciding alone).

H5 The effect of the deciding entity will interact with the data source such that, if both external and internal data are used in (a) a combined human and AI evaluation or (b) an exclusive AI evaluation, privacy intrusion will be higher compared to an exclusive human evaluation that uses only internal data.

Organizational attractiveness and turnover intention. Among various other consequences, two important general outcomes of employees' justice perceptions are their attitudes towards the organization and their withdrawal behavior (Cohen-Charash and Spector 2001; Colquitt 2001). Specifically, employees' justice perceptions are associated with the organization's perceived attractiveness and willingness to stay with the company. Fair treatment of employees is directly linked to the image employees have of their company and can influence the relationship with the company (McCarthy et al. 2017). If employees have a positive overall opinion of the career decision process, they also evaluate their company as attractive (Cropanzano et al. 2007). Conversely, if employees are dissatisfied with the career development process, they may perceive the company as less attractive and may even think about leaving the company (Hausknecht et al. 2004; Nadiri and Tanova 2010; Truxillo and Bauer 2011). Unfairness is like a "corrosive solvent" that can jeopardize bonds within a company (Cropanzano et al. 2007, p. 34). Consequently, we expect that when employees feel mistreated and dissatisfied during the career development process, this has direct detrimental effects on turnover intentions and organizational attractiveness (Bauer et al.

2006, 2020). Furthermore, we expect that if employees fear that their privacy will be invaded during the career development process, they will find their company less attractive and consider leaving. Thus, we hypothesize that fairness, satisfaction with the process, and privacy intrusion are directly associated with organizational attractiveness and turnover intention.

H6 (a) Fairness and (b) satisfaction with the process will be positively related and (c) privacy intrusion will be negatively related to organizational attractiveness.

H7 (a) Fairness and (b) satisfaction with the process will be negatively related and (c) privacy intrusion will be positively related to turnover intentions.

Fairness judgements of individuals are the result of how they evaluate certain events that they experience (Cropanzano et al. 2015). In turn, their subjective evaluation of justice is associated with, for instance, attitudes towards the organization, work behavior, organizational commitment, trust, and withdrawal behavior (Cohen-Charash and Spector 2001; Colquitt et al. 2001). If employees feel treated unfairly, are dissatisfied or have a sense of privacy invasion during a career development process, which is either supported by AI or completely conducted by AI, these justice perceptions should explain (i.e., mediate) the adverse reactions of employees concerning organizational attractiveness and turnover intentions. Similarly, employees' subjective evaluation as a response to the data sources used during the career development process should also explain employees' reactions in terms of organizational attractiveness and turnover intentions. Therefore, we propose that perceived fairness, satisfaction with the process, and privacy intrusion are important mediating mechanisms, which help to explain the individual reactions towards the deciding entity and the data source during career development and, in turn, shape their attitudes towards the organization and the withdrawal behavior.

H8 The association between the deciding entity and organizational attractiveness is partially mediated by (a) fairness, (b) satisfaction with the process, and (c) privacy intrusion.

H9 The association between the deciding entity and turnover intentions is partially mediated by (a) fairness, (b) satisfaction with the process, and (c) privacy intrusion.

H10 The association between the data source and organizational attractiveness is partially mediated by privacy intrusion.

H11 The association between the data source and turnover intentions is partially mediated by privacy intrusion.

3 Overview of studies

We conducted three consecutive studies to test our hypotheses and the causal chain of our proposed mediating mechanisms. First, the *Pilot Study* validates the written scenarios that we developed to answer our research question (Raaijmakers et al. 2015). Second, the *Main Study* builds on the results of the pilot study. For the main study, we used scenarios since they provide an appropriate and valid method to explore feelings and decisions in common situations (Maute and Dubé 1999; Ötting and Maier 2018). We evaluate our experimental design using a structural equation model (SEM), which is an appropriate approach for our specific research aim because it allows us to test the relationships of all included predictors and controls simultaneously (Breitsohl 2019). Third, the *Additional Study* complements the main study's measurement-of-mediation design with an experimental-causal-chain approach (Spencer et al. 2005) to test the causal link between the proposed mediators (i.e., fairness, satisfaction, privacy intrusion) and turnover intention as well as organizational attractiveness.

3.1 Pilot study

With our pilot study, we seek to validate our developed scenarios prior to their implementation in the main study, following recommendations on best current practice approaches in experimental scenarios (Raaijmakers et al. 2015). We wanted to ensure that participants can identify the different types of decision making and data sources used. Based on an extensive literature search, we manipulated the decision maker (human, human, and AI, and AI) and the information available (internal, external, internal and external) for the decision-making process.

3.1.1 Method

Development of our scenarios. The text described an inclusion process into a career development program at the end of the year from the fictitious company *Marzeo*. We chose an inclusion situation because it reflects a common decision in everyday work life. Additionally, the use of written scenarios in an experimental design is an internally valid method if the participants are confronted with realistic situations (Maute and Dubé, 1999). Furthermore, the company name and URL (www.marzeo.de) were developed and used in previous research (Evertz et al. 2021) to ensure that participants would not find any additional information about the company.

In Scenario 1, a committee consisting of representatives of the human resources department, the division manager, and the business manager makes decisions about inclusion into the career development program. In Scenario 2, the committee additionally evaluates internal information manually, such as the start and end of work, absenteeism, overtime, and open vacation days. In Scenario 3, the committee makes decisions about the inclusion into the career development program with the help of the manual evaluation of internal and external data. In addition to the internal data, external data from social networking sites are manually evaluated, such as posts, likes, events, search history, pictures, and added network contacts, that describe the use of external big data. In Scenario 4, the committee and the AI only have the internal information available to them for their decision. These internal data are algorithmically evaluated by an AI system, and this evaluation serves as decision support. Scenario 5 is the same as Scenario 4, with the additional aspect of external data assessment. Again, the final decision about inclusion into the career development program remains human. In Scenario 6, AI decides, with the help of the internal data, about inclusion into the career development program, while in Scenario 7, external data is added (see the Appendix for exemplary scenarios).

Participants and procedure. We recruited 175 German university students to participate in our paper-and-pencil pilot study. In this sample, 52.6 percent ($N=92$) were female, 44.0 percent ($N=77$) were male, and three reported diverse gender. The mean age was 25.02 years. The students were both Bachelor's and Master's students. Some of the students had already gained their first work experience as part of internships and working student activities. Participants were randomly assigned to one of our seven between-subject scenarios that manipulate the entity of the decision and the type of information used to make the decision. We applied a between-subject design using seven scenarios as treatment (Aguinis and Bradley 2014; Charness et al. 2012).

3.1.2 Results and discussion

To ensure high-quality data, we conducted several procedures and checks to exclude various potential biases as recommended by Ejelöv and Luke (2020). First, to enhance data quality, we included two attention checks in our questionnaire. All participants in our sample passed both attention checks (e.g., "For this item, please select "strongly disagree") (Barber et al. 2013; Kung et al. 2018; Ward and Pond 2015). Second, we included two stimulus checks for our treatments at the end of the questionnaire. For the decision maker, participants were instructed to think about the described scenario again and then state who they believed had decided about their career development (human, human and AI, AI). Further, we asked the participants to indicate which data type was included in the decision (internal data, internal and external data, external data). For the decision maker question, 52 participants chose a decision maker not described in their respective scenario. The only systematic error occurred for the scenarios in which the human committee decided without AI. We concluded that the wording for the data did not exclude that these data were received via AI and adjusted the scenario accordingly. For external and internal data, only 19 participants did not report the correct scenario, which is approximately 11 percent. Therefore, only slight modifications were made.

Finally, to ensure that the scenarios are sufficiently realistic, we asked respondents to rate, on a 7-point Likert-scale, the realism (1 = unrealistic to 7 = realistic) and the valence, that is, how well they were able to put themselves into the situation (1 = very bad to 7 = very good). Overall, results show sufficient realism ($M=4.64$; $SD=1.58$) and valence ($M=4.79$; $SD=1.50$). In summary, the pilot study's conclusion suggests that our stimuli for the deciding entity and the source of data function as intended.

3.2 Main study

3.2.1 Method

Participants. We registered our study before data collection at aspredicted.org.[2] Using an online panel of an ISO 20252:19 certified online sample provider, we recruited a working sample, with sex and age approximating the respective distributions in the German general sample whose sex and age approximated the respective distributions in the German general population, with a total of 280 participants (aiming for 40 participants per condition). The sample was composed of 48.9 percent ($N = 137$) females, 50 percent ($N = 140$) males, and three participants with a diverse gender. The mean age was 44.9 years. All participants were currently working and reported an average working experience of 23.26 years ($SD = 13.81$). Concerning the highest educational qualification, 11.4 percent had a high school diploma or equivalent, 51.8 percent had finished an apprenticeship, 11.4 percent had a bachelor's degree, 21.4 percent had a master's degree, 0.7 percent had a doctoral degree, and 3.6 percent reported other degrees.

Design and procedure. We applied a between-subject design to test our hypotheses using seven hypothetical scenarios for our treatment (Aguinis and Bradley 2014; Charness et al. 2012) (see the Appendix for example scenarios). Participants were randomly assigned to one of our seven revised between-subject scenarios and completed a questionnaire containing all measures. Participants completed our experimental vignette study online in their free time.

Measures. We measured all scales with items that ranged from 1 (*strongly disagree*) to 7 (*strongly agree*). To reduce common method bias, the items for the scales and measures were rotated to exclude a certain response behavior due to the sequence of the items. All scales were adopted from existing measures to ensure the reliability and validity of our measures. Additionally, we adapted the items to the company *Marzeo* used in the scenarios.

Satisfaction with the evaluation process. Overall satisfaction with the evaluation process was measured with two items adapted from Wehner et al. (2015) and one self-developed item. The items were "All in all, I am satisfied with the assessment process," "The process corresponds to my ideas of an ideal assessment process," and the self-developed item was "I like this assessment process." Cronbach's alpha of the satisfaction scale was 0.95.

Fairness. We measured this variable with one item from the selection procedural justice scale from Bauer et al. (2001) and additional two items from Warszta (2012). Items were, for example, "I think the evaluation process itself is fair." Cronbach's alpha of the fairness scale was 0.92.

Privacy intrusion. This variable was based on Xu et al. (2008). The three items were "I feel that by evaluating the data, others know about me more than I am comfortable with," "I believe that as a result of the evaluation, the information about me that I consider private is now more readily available to others than I would want it to

[2] http://aspredicted.org/blind.php?x=898ii8.

be," and "I feel that as a result of the evaluation process, the information about me is out there that, if used, will invade my privacy." Cronbach's alpha of the privacy intrusion scale was 0.86.

Job turnover intention. We measured this variable with two items from Walsh et al. (1985). The two adapted items were "I am thinking about quitting Marzeo," and "I would look to see if any positions in other firms are open." Cronbach's alpha of the job turnover intention scale was 0.88.

Organizational attractiveness. This variable was measured with three items from Aiman-Smith et al. (2001). Again, we adapted the items to the company *Marzeo* used in the scenarios. The three adapted items were "The company Marzeo is a good company to work for," "The company Marzeo cares about its employees," and "I find the company Marzeo a very attractive company." Cronbach's alpha of the organizational attractiveness scale was 0.94.

Control variables. It seems reasonable that participants who are interested in new technologies and like to experiment with new technological innovations are more inclined to positively evaluate and perceive the use of AI in career development. Therefore, we measured technological affinity with three items of the "personal innovativeness in the domain of information technology" scale from Agarwal and Prasad (1998). Cronbach's alpha of the technological affinity scale was 0.88. In addition, we controlled for negative affectivity (Cronbach's alpha = 0.86), gender, age, highest educational qualifications, and working experience, variables that are likely to influence the perception and evaluation of AI and the use of external data during the decision about inclusion into the career development program.

Analytical procedures. Concerning data analyses, we used a two-step approach (Anderson and Gerbing 1988). First, we estimated the confirmatory factor analysis (CFA) and included our observed treatment, interaction variables, and latent control variables as covariates in the measurement model. Second, we evaluated the SEM to test the hypotheses on potential mediation (Breitsohl 2019). We used chi-square statistics and fit indices to assess the model fit to the data (Bollen 1989; Browne and Cudeck 1992; Hu and Bentler 1998; Kline 2015; Mulaik 2009). A well-fitting model should have a nonsignificant chi-square ($\chi 2$) test (Bollen 1989), a comparative fit index (CFI) above 0 0.95 (Hu and Bentler 1998), and a root mean square error of approximation (RMSEA) below 0.06 (Browne and Cudeck 1992).

The results of our CFA exhibit satisfactory model fit. Although the $\chi 2$ test is significant ($\chi 2(149) = 224.183$, $p = 0.001$), the fit indices indicate that the seven-factor model fits the data well, with CFI = 0.98, SRMR = 0.027, RMSEA = 0.042, and all standardized factor loadings > 0.74.

3.2.2 Results

Descriptive statistics. Table 1 shows the means, standard deviations, and correlations of our variables.

Results of the SEM. Table 2 shows the estimated coefficients of the SEM. Again, the SEM exhibits a satisfactory model fit. Even though the $\chi 2$ test is still significant ($\chi 2(149) = 224.183$, $p = 0.001$), the fit indices indicate that the model fits the data well, with CFI = 0 0.97, SRMR = 0.041, RMSEA = 0.044, and all standardized factor

Table 1 Main Study: Means, standard deviations, and correlations

	Variable	Mean	SD	1	2	3	4	5	6	7	8	9	10
1	Age	44.93	13.49	–									
2	Gender	1.52	0.52	.08	–								
3	Educational background	3.59	1.17	.12*	.16**	–							
4	Negative affectivity	2.61	1.36	−.24**	−.04	−.05	*.88*						
5	Technological affinity	4.33	1.39	−.03	.08	.09	−.27**	*.86*					
6	Satisfaction with process	3.44	1.64	−.07	.08	−.10	−.03	.24**	*.95*				
7	Fairness	4.14	1.29	.01	.05	−.06	−.08	.23**	.72**	*.92*			
8	Privacy intrusion	4.64	0.86	.06	−.08	−.10	.07	.03	−.17**	−.17**	*.86*		
9	Turnover intention	4.37	1.71	.07	−.09	.12*	.06	.00	−.54**	−.51**	.42**	*.88*	
10	Organizational attractiveness	3.95	1.39	−.15*	.04	−.08	−.08	.33**	.64**	.65**	−.10	−.50**	*.94*

** $p<0.01$, * $p<0.05$. On the diagonal, Cronbach's alpha is reported

Table 2 Main study: direct, indirect and total effects of the decision agent and social media

Dependent variable	Perceived fairness	Privacy intrusion	Satisfaction with the process	Organizational attractiveness	Turnover intention
Direct effects					
Human & AI (Ref. Human)	**−.136 [−.237; −.036]**	**.200 [.097; .300]**	**−.132 [−.228; −.032]**		
AI (Ref. Human)	**−.273 [−.379; −.166]**	**.277 [.117; .341]**	**−.320 [−.426; −.214]**		
Int & Ext Data (Ref. Int Data)	**−.233 [−.328; −.141]**	**.301 [.204; .398]**	**−.153 [−.251; −.057]**		
Age	−.080 [−.269; .100]	.108 [−.076; .284]	−.058 [−.247; .125]	−.068 [−.212; .069]	**.163 [.014; .322]**
Gender	.086 [−.007; .176]	**−.126 [−.223; −.028]**	.085 [−.007; .175]	−.017 [−.093; .056]	−.044 [−.119; .033]
Educational background	**−.125 [−.223; −.023]**	.028 [−.078; .135]	**−.118 [−.213; −.018]**	−.016 [−.094; .067]	−.052 [−.029; .130]
Technological affinity	**.290 [.181; .393]**	−.044 [−.153; .066]	**.233 [.119; .339]**	**.195 [.112; .278]**	**.106 [.013; .198]**
Negative affectivity	.057 [−.073; .181]	.053 [−.067; .174]	.020 [−.103; .137]	.−.031 [−.118; .056]	.079 [−.015; .166]
Perceived fairness				**.617 [.424; .846]**	**−.367 [−.632; −.117]**
Satisfaction				.049 [−.186: .244]	−.002 [−.248; .258]
Privacy intrusion				−.045 [−.149; .062]	**.503 [.369; .629]**
Total effect of Human &AI				**−.099 [−.170; −.028]**	**.150 [.072; .224]**
throughperceivedfairness				**−.084 [−.160; −.021]**	**.050 [.006; .107]**
through satisfaction				−.006 [−.038;. 025]	.000 [−.039; .033]
through privacy intrusion				−.009 [−.032; .012]	**.100 [.047; .157]**
Total effect of AI				**−.194 [−.272; −.120]**	**.215 [.130; .304]**
through perceived fairness				**−.169 [−.273; −.089]**	**.100 [.029; .189]**
through satisfaction				−.016 [−.081; .061]	.001 [−.083; .083]
through privacy intrusion				−.010 [−.038; .014]	**.114 [.055; .180]**
Total effect of Int & Ext Data (Ref. Int Data)				**−.164 [−.237; −.097]**	**.237 [.162; .310]**
through perceived fairness				**−.143 [−.230; −.075]**	**.085 [.024; .163]**
through satisfaction				−.007 [−.042; .029]	.000 [−.044; .041]
through privacy intrusion				−.013 [−.047; .018]	**.151 [.091; .218]**

Regression coefficients are the standardized estimates. The 95% confidence intervals were computed with 5,000 bootstrapped samples

Indirect effects for which zero was not included in the 95% confidence interval are marked in bold, as no *p* value is provided. The nonsignificant interactions (H5) are not included loadings > 0.74. Both fairness and satisfaction are negatively influenced by the entity that decides about inclusion into the career development program. In particular, in comparison to the human decision, perception of fairness and satisfaction were lower in the condition of humans supported by AI ($\beta = -0.136$, 95% CI [−0.237, −0.036]; $\beta = -0.132$, 95% CI [−0.228, −0.032]) and lowest in the AI decision ($\beta = -0.273$, 95% CI [−0.379, −0.166]; $\beta = -0.320$, 95% CI [−0.426, −0.214]), supporting both H1a and H1b and H2a and H2b. Moreover, when compared to the decision made by a human alone, the perceived privacy intrusion was higher in the entity condition of humans supported by AI ($\beta = 0.200$, 95% CI [0.097,0.300]) and highest in the AI decision ($\beta = 0.277$, 95% CI [0.117,0.341]), thus supporting H3a and H3b. In addition, the data source was positively associated with privacy intrusion ($\beta = 0.301$, 95% CI [0.204,0.398]), supporting H4. Although we did not hypothesize these effects, the data source also showed negative associations with perceived fairness ($\beta = -0.233$, 95% CI [−0.328, −0.141]) and satisfaction with the process ($\beta = -0.153$, 95% CI [−0.251, −0.057]). Yet, the interaction between the data source and the deciding entity was nonsignificant, indicating that the data source does not strengthen the influence of the deciding entity on privacy intrusion, rejecting H5a and H5b. Given the significant associations with perceived fairness and satisfaction, we also tested interactions between the data source and the deciding entity for these outcomes, but all interactions were nonsignificant.

In turn, fairness was positively associated with attractiveness ($\beta = 0.617$, 95% CI [0.424,0.846]) and negatively associated with turnover intentions ($\beta = -0.367$, 95% CI [−0.632, −0.117]), supporting H6a and H7a. In contrast, satisfaction was neither related to attractiveness ($\beta = 0.049$, 95% CI [−0.186, 0.244]) nor turnover intentions ($\beta = -0.002$, 95% CI [−0.248,0.258]), rejecting H6b and H7b. Finally, privacy intrusion was unrelated to attractiveness ($\beta = -0.045$, 95% CI [−0.149, 0.062]), rejecting H6c; however, privacy intrusion was positively associated with turnover intentions ($\beta = 0.503$, 95% CI [0.369, 0.629]), supporting H7c.

Concerning our mediator hypotheses, both human and AI evaluation as well as the AI evaluation conditions (i.e., the deciding entity) were associated with reduced organizational attractiveness and increased turnover intention through perceived fairness, supporting H8a and H9a. Additionally, the deciding entity showed a positive association with turnover intentions through privacy intrusion, supporting H9c. However, we found neither an association between the deciding entity and organizational attractiveness through satisfaction and privacy intrusion (i.e., rejecting H8b and H9b) nor between the deciding entity and turnover intentions through satisfaction, rejecting H9c. Overall, the total effects for the AI evaluation on the outcomes were slightly higher than for the human and AI evaluation, which indicates that the inclusion of AI in decision-making should be considered carefully. The external and internal data condition (i.e., data source) was associated with increased turnover intention through perceived privacy, supporting H11, while we found no effect on organizational attractiveness through privacy intrusion, rejecting H10. Nevertheless, data source showed significant total effects on organizational attractiveness and turnover intentions through perceived fairness and satisfaction, which we did not hypothesize. Finally, individuals with higher technological affinity were more satisfied with the process and perceived it as fairer. Interestingly, technological affinity was unrelated to the perceived privacy intrusion. Figure 2 depicts the results of the Main Study graphically.

3.3 Additional study

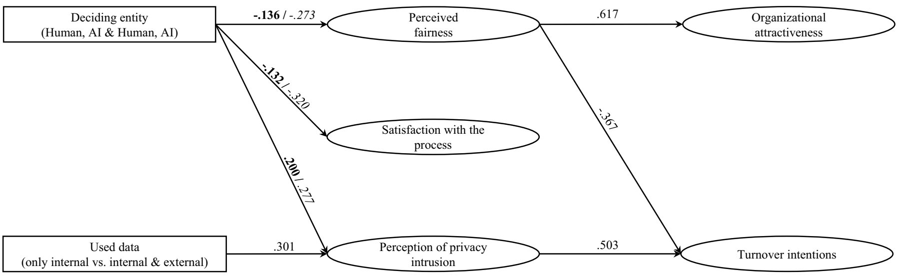
Following Spencer et al. (2005), we complemented the main study's measurement-of-mediation design with an experimental-causal-chain approach, testing the causal link from fairness, satisfaction, and privacy intrusion on turnover intention and organizational attractiveness, as implied by our hypotheses. The experimental-causal chain approach is useful when testing mediation in an experiment since in an experiment that manipulates relationships between the independent variables (factors) IV, the mediators (M) and the outcomes (O), the relationship between M and O are not causal in nature, as both are simultaneously measured after the manipulation. To overcome this, the next step in the chain is to manipulate M in an additional experiment, which then links M (as new IV) to O, which provides evidence for the causal effect. In combination, this tests the mediation more thoroughly than just using a single experiment.

Therefore, we manipulated fairness (fair/unfair), satisfaction (satisfied/unsatisfied), and privacy intrusion (low/high) of the same career development process described in the main study (see the Appendix for example scenarios). Based on a working population sample ($N=157$) including 84 female and 73 male participants with a mean work experience of 20.59 years ($SD=13.11$), we replicated the results of the main study.

To that end, we used the same measures for attractiveness (Cronbach's alpha = 0.95) and turnover intention (Cronbach's alpha = 0.94) as in the main study. We calculated independent t-tests in IBM SPSS 26 and found that fairness had a positive effect on organizational attractiveness (supporting H6a: $t(43)=4.48$, $p<0.001$) and a negative effect on turnover intention (supporting H7a: $t(43)=-6.34$, $p<0.001$). Also, we found that privacy intrusion had a positive effect on turnover intention (supporting H7c: $t(31)= -2.28$, $p<0.05$). Both findings support the causal relationship suggested for fairness and privacy intrusion in Hypotheses 5 and 6, respectively. Interestingly, when not controlling for the other mediating mechanisms, satisfaction had the same significant effects as perceived fairness on attractiveness ($t(33)=4.65$, $p<0.001$) and turnover intentions ($t(33)= -4.80$, $p<0.001$) and privacy intrusion also had a negative effect on organizational attractiveness ($t(31)=4.33$, $p<0.001$).

4 General discussion

AI is increasingly used as a decision-making tool in the career development of large companies. The usage of these tools increased by the shifts in the way work is conducted and the increased reliance on technology, caused by the pandemic. We investigated whether different decision agents and different data sources led to adverse employee reactions. In comparison to a human decision, we consistently found that



Note. The interaction between the deciding entity and the data (H5) was removed due to insignificance, as well as the insignificanteffects of the mediators. For the sake of parsimony, the assumed mediations and control variables are not displayed. Regression coefficients are the standardized estimates. Regarding the Deciding entity, bold coefficients are Human & AI (with the reference solely Human), and italic coefficients are AI (with the reference solely Human). See table 2 for detailed results.

Fig. 2 Presentation of the results of the main study

fairness, satisfaction with the process, and privacy intrusion are influenced by the degree to which an AI system is supporting or even deciding about career development. Surprisingly, the data source does not strengthen the negative impact of the deciding entity. In turn, fairness was positively (negatively) associated with company attractiveness (turnover intentions), while privacy intrusion increased turnover intentions. Satisfaction with the process seemed to be unrelated to company attractiveness and turnover intentions in this particular context. These findings have important theoretical and practical implications concerning adverse employee reactions to the use of AI systems in career development.

4.1 Theoretical implications

The findings of the study have important theoretical implications, as the knowledge of adverse employee reactions to the usage of AI in HRM is still in its infancy (Cheng and Hackett 2021; Köchling and Wehner 2020; Newman et al. 2020; Santana and Díaz-Fernández 2023; Wirges and Neyer 2023). First, we contribute to the current debate on fairness perceptions and employee reactions when AI is involved in HR (Cheng and Hackett 2021; Karim et al. 2015; Ötting and Maier 2018). By showing that the inclusion of AI into the career decision negatively influences employee reactions, we add to the existing knowledge on the detrimental effects of AI in the context of HRM that jeopardizes the implementation of AI into the career decision-making processes (Stone et al. 2015).

Second, our findings support the notion that fairness is an important mediating mechanism in explaining the negative reaction towards organizational attractiveness (e.g., Acikgoz et al. 2020; Köchling et al. 2023; Köchling and Wehner 2023; Langer et al. 2018). We extend this knowledge by showing that fairness is also mediating the detrimental effects of AI usage in career development on company attractiveness and turnover intentions, which helps to explain why employees find the organization less attractive and might leave the organization if AI is used during career development. Besides the well-known mechanism of fairness (Lee 2018), we also find that privacy intrusion mediates the detrimental effects of AI usage on turnover intentions. Privacy concerns arise when using AI for decision making because it might be not consistent with the ethical norms of the employees. Hence, privacy concerns and the perception of intrusion into one's personal information space seem to have a stronger influence on the individual's decision to leave the company than on the general attractiveness of an organization as an employer.

Third, our findings provide a deeper understanding of the role of the deciding entity. Although an automated evaluation process appears to be more valid, given that human raters may assess candidates inconsistently or without adequate evidence (Kuncel et al. 2013; Woods et al. 2020), the support of AI, as well as an automated decision by AI, leads to negative employee reactions. The results show that it is not a question of whether the process is statistically fairer, but rather what the employees rate to be fair, ethical, and satisfying as the perception of the process is rather subjective than objective (Cropanzano et al. 2007). Also, the aspect of humanity is essential when it comes to career decisions or decisions about the potential of an individual (Lee 2018). Humanity is missing when an AI decides alone, and the employees might lack interpersonal contact and they might not feel valued when the process is supported or conducted purely by an AI.

Finally, we answered the call for research how HR departments should manage employee´s private data by Santana and Díaz-Fernández (2023) and provide evidence that increased volume and increased variety of data, in this context the addition of external data, was also associated with feelings of dissatisfaction, privacy intrusion, and unfairness perceptions, which, in turn, diminished organizational attractiveness and increased turnover intentions. When using external data for career development decisions, ethical and privacy concerns can arise (Stoughton et al. 2015) because the use of external data is against the expectations of employees (Mgrditchian 2015). In turn, this leads to lower satisfaction and fairness perception and higher privacy intrusion. Hence, the question of what kind of personal information should be used to train AI and assess employees for career development is as important as the question of who decides about an employee's potential and talent.

4.2 Practical implications

From a managerial perspective, our findings have substantial implications for HR managers. AI-based career development tools have several advantages from an organizational perspective (e.g., efficient, cost-saving). However, organizations that decide to delegate their career development to an AI should also consider the potential adverse effects on employees' reactions. More broadly, our results have important implications for strategic HRM and urge caution for the implementation of AI in career development. Our results can help organizations to decide wisely on whether, how, and to what extent AI applications should be used. AI use in career development can have negative consequences for the perceived fairness, the satisfaction with the process, and the perceived privacy intrusion, especially if the AI application makes decisions without human input. Managers must be made aware that employees may feel unfairly treated due to the decision agent. Additionally, managers should be aware that the use of AI alone is not beneficial for the company's attractiveness and turnover intention.

When AI is involved in the career management context, managers should try to explain the career decision to the employees in person and explain the reasons for the decision even if the decision was conducted by an AI. This explanation could decrease the feeling of not being valued when an AI is used and consequently increase satisfaction.

We show that using external data for career development can have negative consequences such as lower company attractiveness. Thus, HR managers should try to avoid the use of external data, especially as the benefits of including such information for career decisions are still underdeveloped. Moreover, managers should be aware that the use of external data for career decisions can be illegal in some countries and could lead to the opposite company corporate image as desired. If managers still want to use external data, employees should be given a transparent explanation of what data is used and in which ways, so that the employee can calculate the benefit of the use of the data more clearly (Bhave et al. 2020).

The findings suggest that AI applications should be implemented with caution. It could be helpful to implement the new systems in cooperation with the employees. Besides, managers could explain the new technologies and processes to their employees (Köchling and Wehner 2020, 2023; Leicht-Deobald et al. 2019; Tambe et al. 2019). Consequently, HR managers need to make the process more transparent, for example, by explaining how the AI supports human decisions or even how the AI makes decisions. The knowledge about the algorithm's way of making decisions might change the employees' perception of this technology.

4.3 Limitations and directions for future research

We put much effort in ensuring that the design of the studies allowed us to minimize the risk of potential biases (Podsakoff et al. 2012). First, written scenarios provide an appropriate method to explore attitudes and feelings as well as to gain insights into decisions as suggested by previous research (Maute and Dubé, 1999). Moreover, our causal-chain analysis enabled us to test causality. However, the design of the study was an online experimental vignette study; therefore, it did not allow for an actual firsthand experience of the situation. Consequently, future studies could test employee reactions towards AI in career development in real-life settings, for example, in organizations that already use AI in their career management. Second, data collection took place in Germany. Germany has specific characteristics concerning its culture (for the cultural profile, see Hofstede et al. 2010), labor market (e.g., employee organizations)), and specific data protection laws that might constrain the generalizability of the results to other cultural or institutional environments. Thus, future research should assess the research question in other countries with employees of different nationalities. Third, the participants just got the information that data from social networks is used, which increases the volume and variety of the used data for the decision. However, we did not provide information to the participants about the kind of external data that was used. This could be one reason why the usage of external data, meaning increased volume and variety of data did not strengthen the negative impact of AI involvement. In the extant literature, a distinction between private social media (e.g., TikTok, Instagram, and Facebook) and professional social media (e.g., LinkedIn) is made (Hartwell and Campion 2020; Roulin and Bangerter 2013). Previous research in the recruitment context has shown that applicants have more favorable perceptions when, in contrast to private media, professional data, such as LinkedIn, are used because employees built them for professional use and expect employers to take this information into consideration (e.g., Cook et al. 2020; Roulin and Bangerter 2013). Thus, future studies could shed light on whether the kind of social media that is used to make a career decision exerts an influence on this decision.

In addition to the limitations of our study, our findings also indicate several additional aspects that future research could focus on. First, the growing application of AI use in HRM (and with it the growing familiarity with these tools) might change the acceptance of these tools over time. With that, negative reactions to such tools might diminish, especially as AI is becoming increasingly salient in the daily life of individuals and when the perceived value increases (Sohn and Kwon 2020). Second, future research could examine if, and to what extent, managers are influenced by the decision support of an AI and how they take these AI-based recommendations into account in their own decision. We showed that the interaction between human and AI was less detrimental than the pure AI situation, so a fruitful way might be to combine the strengths attributed to both entities. Third, while the human-AI interaction also might increase AI acceptance, the research could analyze what organizations can do to increase it further in the context of career development systems. Possible avenues could be increasing the transparency regarding the implementation process and the usage of AI, recruiting active employee participation in the planning, and providing more detailed information about how the AI system works (the information it uses, weighting, etc.) (Köchling and Wehner 2020).

5 Conclusion

Through a unique experimental scenario, we set out to provide insights on the employee reactions to AI applications and excessive data availability in career development. This is important given the increasing usage of AI and the availability of extensive internal and external data in organizations as well as the ongoing debate on adverse employee reactions to AI in HRM, which is still in its infancy. Consequently, there is a need to assess the degree to which AI applications enable organizations to motivate and retain their current and talented employees. We first demonstrated that perceived fairness and satisfaction are lowest and privacy intrusion is highest if an AI agent solely decides, without human influence, on the inclusion into a promotion program. Having clarified our supposition, we then determined that the data source does not strengthen the negative impact. By demonstrating that AI applications in career development can lower employees' perceived fairness and satisfaction, and increase the sense of privacy intrusion, we emphasize that AI applications are best used as decision support tools and not as the sole decision maker. As such, we highlight the importance of humans as final decision makers, and we advocate for a carefully considered implementation of AI applications.

Appendix

Scenarios for the main study

Introduction (the same for all participants):

You work for Marzeo, an internationally active manufacturer of commercial goods. As part of the project team, you will be involved in an international campaign for the company. At the beginning of each year, goals which you are to achieve during the course of the year are agreed upon. Besides, there is the possibility of receiving special support within the company. In addition to personal and professional development opportunities through a customized mentoring and career program, this includes several other benefits. For example, you would take on more responsibility and would also receive a salary increase as a result. Whether you are accepted into the promotion program depends on your assessment.

The assessment process is as follows:

Example: exclusive human decision (no internal or external data)

A committee consisting of representatives of the human resources department, your division manager, and your business manager will draw up a brief report on you. The report is based on the committee's assessment of your performance, the achievement of the agreed objectives, and your working methods over the past year.

Based on the report, the committee decides whether you will be accepted into the promotion program and notifies you by email.

Example: human decision supported by AI with internal data

A committee consisting of representatives of the human resources department, your division manager, and your business manager will draw up a brief report on you. The report is based on the committee's assessment of your performance, the achievement of the agreed objectives, and your working methods over the past year.

In addition to the subjective assessment, other internal company data such as start and end of work, sick leave, overtime, and remaining vacation are taken into account. The data is evaluated algorithmically by an artificial intelligence application, which makes a recommendation. There is no further external data available for the preparation of the report.

Based on the report, the committee decides whether you will be accepted into the promotion program and notifies you by email.

Example: exclusive AI decision with internal data and external data

An artificial intelligence application will prepare a brief report on you. The report is based on your performance, the achievement of the agreed goals, and your working methods in the past year.

In addition, the artificial intelligence application takes into account other internal company data, such as start and end of work, sick leave, and remaining vacation time. The artificial intelligence application also has access to other external data from your private social networks, such as your likes, posts, events, search history, images, and added network contacts. The internal and external data are algorithmically evaluated by artificial intelligence. Based on the report, the system decides whether you will be accepted into the promotion program and notifies you by email.

Scenarios for the causal-chain analysis

The introduction was the same as for the main study.

Example: satisfied

All in all, you are very satisfied with the evaluation process. The process meets your expectations of an ideal evaluation process. Although you have not yet been informed of the result, you are pleased with the entire process.

Example: unfairness

All in all, this evaluation process seems very unfair to you. You have the feeling that a clear difference is made in how the employees are treated in the evaluation process and not all are evaluated in the same way. Overall, you think that this evaluation process is not a fair way to select employees for this special career development program in the company. In your view, the process is tainted with clear prejudices and is inappropriate.

Example: low privacy intrusion

All in all, you believe that any information about you that you consider private will be treated confidentially during the evaluation process. The data is protected from unauthorized access, and the available information seems to have a very minimal effect on your privacy or not at all.

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