Rising like a Phoenix: Emerging from the Pandemic and Reshaping Human Endeavors with Digital Technologies ICIS 2023

IT Implementation and Adoption

Dec 11th, 12:00 AM

Navigating AI in Personnel Selection: A Scenario-based Study on Applicants' Perceptions

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Completed Research Paper

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Abstract

AI-based systems are increasingly deployed on organizational tasks, such as personnel selection decisions. As existing research indicates that applicants generally react negatively to the use of AI in personnel selection, this study examines how organizations can mitigate adverse reactions to fully exploit the benefits of AI. To obtain robust results, we recruited an online sample of German participants (N = 1,852) and presented them with various selection scenarios. Using a between-subject design, the process stage (pre-selection vs. interview) and the degree of process automation (augmented vs. automated) were manipulated. By employing a multidimensional conceptualization of transparency, we show that disclosure and accuracy positively impact procedural justice perceptions, a strong predictor of process quality assessment. This relationship is robust across selection contexts. Results indicate that applicants prefer AI for pre-selection and as human decision support, thus offering overall insights into design choices for AI in selection, optimizing applicant reactions.

Keywords: AI, personnel selection, applicant reactions, transparency, procedural justice, process quality

Introduction

Fueled by technological advances, systems based on artificial intelligence (AI) are increasingly used to support or autonomously make organizational decisions, including strategic personnel decisions such as personnel selection (Glikson & Woolley, 2020; Lee, 2018). In doing so, these systems offer great potential in terms of increased effectiveness, objectivity, convenience, and reduced costs, and redefine interactions between individuals and organizations (Köchling & Wehner, 2020). While lacking a unified definition, AI has recently been described as "the frontier of computational advancements that references human intelligence in addressing ever more complex decision-making problems" (Berente et al., 2021, p. 1435). Thus, AI refers to machines executing a range of cognitive tasks typically linked to human intelligence and encompasses diverse approaches, such as rule-based symbolic logic and machine learning. This study focuses on systems as applications of weak AI that stimulate intelligent behavior in a particular domain and considers specifically the use of machine learning to identify suitable candidates among job applicants

(Hofeditz et al., 2022; Russel & Norvig, 2016). The application of AI-based systems in personnel selection is particularly interesting for two main reasons. First, in a knowledge-based economy with a shortage of skilled workers, talent recruitment has gained strategic importance for firm success (Acikgoz et al., 2020; van Esch et al., 2019). Second, unlike consumers, who have a choice to interact with or rely on AI-based systems, job candidates are, in practice, forced to follow the corporate process, leading to changes in the power structure, which may affect perceptions of AI-based systems and the hiring firm (Lee, 2018). Further, those AI-based systems could be perceived as discriminatory or value-laden due to biased training data or unobservable mechanisms (Köchling & Wehner, 2020). In line with the concept of algorithm aversion, proposing that people are reluctant to rely on algorithms (such as AI-based systems) that perform tasks typically done by humans (Dietvorst et al., 2015), existing research suggests that applicants typically respond unfavorably to selection processes that involve AI-based systems (Langer & Landers, 2021). While to improve AI-based systems, researchers are progressively working to identify and eliminate bias, that alone is insufficient. Unfavorable reactions can spill over to important hiring-related outcomes, such as applicants' evaluation of the firm's attractiveness and their willingness to pursue the position or to accept the offer (Truxillo et al., 2009). So, to allow organizations to fully exploit the potential efficiency and validity gains from automation without being disadvantaged in the war for talent, applicants need to evaluate AI-based selection processes positively regardless of the actual performance of the AI-based systems.

Against this background, the question arises as to how personnel selection processes involving AI-based systems should be designed and how applicant reactions can be positively influenced. Applicant reactions mirror how job candidates perceive and respond to the hiring process or selection tool based on their experience (McCarthy et al., 2017). In this study, we focus on the applicants' perceptions of procedural justice and their evaluation of the process' overall quality. As highlighted by justice research in personnel selection contexts, justice perceptions are a key driver that determines applicants' responses to selection procedures (McCarthy et al., 2017). In line with this, perceptions of procedural justice have gained increasing attention in emerging research on AI-based selection procedures. Nevertheless, there are few studies focusing on understanding the mechanisms that shape these perceptions of procedural justice (Acikgoz et al., 2020; Langer & Landers, 2021). In existing research on applicant reactions to traditional selection processes involving human decision-makers, providing information about the process has proven to be a cost-effective method for enhancing applicants' responses to these procedures (Truxillo et al., 2009). However, the generally positive outlook regarding using information to foster favorable applicant reactions needs further qualification in the context of AI-based procedures. The available findings exploring the extent to which offering information about the application process impacts applicant reactions are limited and inconsistent, falling short of the positive outcomes observed in human decision-making contexts. Instead, studies have found either a negative effect of providing information on perceptions of procedural justice or no significant effect at all (Langer et al., 2018; Newman et al., 2020; Wesche et al., 2022).

In this study we argue that applicants' perceptions of procedural justice and, thus, reactions towards AI-based selection processes are positively influenced by the perceived quality of shared information (i.e., transparency), as previous research has shown that this has the potential to enhance reactions to technology-based selection processes (Langer & König, 2023; Langer et al., 2018). Contrary to previous studies, we refer to recent transparency research (e.g., Schnackenberg et al., 2021) and include the multidimensionality of perceived information quality in our study. Following initial evidence suggesting that applicant reactions depend on contextual factors, we examine the proposed relationship in different contextual settings (Gonzalez et al., 2022; Langer & Landers, 2021), examining whether reactions towards AI-based selection processes are influenced by a) the degree of process automation and b) the process stage. Regarding the first of these, we differentiate between decisions made purely by an AI-based system without human intervention (automated process) or decisions jointly made by an AI-based system and a human recruiter responsible for the final decision (augmented process). For the process stage we consider the pre-selection stage, where certain information in written application documents is identified and evaluated, and a job interview, where personality profiles of applicants are created. By doing so, we aim to test the generalizability of our proposed relationships. The following research questions (RQs) are posed:

RQ1: Do perceptions about transparency and procedural justice affect applicants' evaluations of the selection process?

RQ2: Are there differences in effect sizes of the relationships considered in RQ1 depending on the degree of process automation and the process stage?

To address these questions, we apply the theoretical lens of organizational justice research and derive hypotheses about the relationships of transparency, procedural justice, and applicants' evaluations of process quality. We test our hypotheses using a quantitative online survey with hypothetical personnel selection scenarios (2x2 between-subject design). Within the survey, 1,852 German participants who are representative for the population in terms of age and gender were presented with a simulation of a selection situation. Participants were provided with textual and visual stimuli with varying degrees of process automation (augmented process vs. automated process) and the process stage (pre-selection vs. job interview) and surveyed on their evaluations. In the statistical analysis, we first compare mean values of all constructs between all scenarios and then test the hypothesized relationships using partial least squares structural equation models (PLS-SEM) for all four scenarios separately. We also compare effect sizes between the scenarios using multi-group analysis (MGA) to determine whether the same relationships exist between the constructs for different contextual factors.

Our study makes three significant contributions to research. First, it emphasizes the crucial role of procedural justice perceptions in shaping applicant reactions to AI-based personnel selection processes and introduces process quality as a novel consequence of procedural justice. Second, the study investigates four distinct configurations of AI-based personnel selection procedures, offering a more nuanced perspective on process automation and human intervention possibilities. By examining various process stages, which were not previously explored in the existing research, our study enriches the understanding of applicant reactions across different stages of the selection process. Finally, the research supports a multidimensional understanding of transparency, focusing on the effects of disclosure, clarity, and accuracy on procedural justice in the context of AI-based systems.

The paper proceeds as follows. The next section provides a brief overview of recent research in the literature on applicant reactions towards selection procedures and introduces the theoretical lens of organizational justice. We then formulate our hypotheses and present the research model. Following that, we outline our methodological approach and research results. In the concluding sections, we discuss the results, their implications, the study's limitations, and potential avenues for future research.

Related Research and Theoretical Foundation

Related Research

Research on applicant reactions towards traditional selection processes typically relied on Gilliland's (1993) model, rooted in organizational justice theory. The well-established model suggests that besides formal characteristics of the selection process and interpersonal treatment during selection, information about the decision-making process is critical in shaping perceptions of procedural justice. These perceptions, in turn, affect applicant reactions during and after the hiring process (Gilliland, 1993). Although studies have moved beyond Gilliland's (1993) model and base their propositions on new theoretical lenses (McCarthy et al., 2017), subsequent research focusing on procedural justice and the impact of information as a promising and cost-effective way to improve applicant reactions towards a selection process proliferated. Truxillo et al. (2009) provided meta-analytical support showing that supplying process information (e.g., job relevance of, or what happens during, a selection procedure) helps to foster procedural justice perceptions and thus, applicant reactions towards the procedure and the organization.

While the positive effect of information on procedural justice and applicant reactions has been confirmed for technology-mediated selection methods (Basch & Melchers, 2019), the extent to which these findings, which stem from research on human decision-making, can be extrapolated to AI-based decision-making remains unclear (Schlicker et al., 2021). Given that applicants may perceive fewer opportunities for process control in AI-based decision processes, such as active participation or appeal processes, resulting in lower procedural justice (Langer & Landers, 2021), information becomes even more critical for enhancing procedural justice perceptions and ultimately, applicant reactions. However, existing research in this area is still limited and inconclusive. For instance, Newman et al. (2020) found that providing applicants with information about what will happen during the process of an automated job interview negatively affected their perceptions of procedural justice. This effect was reversed in the case of human decision-making. Langer et al. (2018) and Wesche et al. (2022) provided applicants with similar procedural information about an automated job interview, but found no effect on perceptions of procedural justice. The authors theorized that certain parts of the information provided might enhance individuals' reactions to AI-based decision-making, while other parts could undermine these positive effects (Langer et al., 2018). However, since these studies have experimentally manipulated the amount of information provided, they were not able to investigate how information should be designed to favorably impact applicant reactions. Referring to recent research on information quality (i.e., transparency; Schnackenberg & Tomlinson, 2016), there are distinct facets of available information which lead to individuals' perception of information quality. Therefore, in organizational as well as in IS research the construct is commonly studied multidimensionally (Lee et al., 2002; Schnackenberg & Tomlinson, 2016).

Overall, existing research highlights the importance of information and the need to explore the conditions under which it can enhance applicant reactions towards AI-based selection procedures, an area where understanding is still limited. Various contextual factors, upon which increasing evidence suggests that individuals' reactions to AI-based procedures are contingent, should be considered. For instance, task-related characteristics, such as the perceived need for human or mechanical skills, the perceived level of quantifiability of task-related information, or the perceived importance of the task, may affect people's reactions (Langer & Landers, 2021). One explanatory approach is offered by the Machines are better at vs. Humans are better at (MABA-HABA) framework, which states that distinct decision-makers have inherent advantages in specific tasks. While AI-based systems might perform more efficiently than humans in mechanical and computational tasks, they are perceived as less capable of making subjective judgments or engaging in social interactions (Glikson & Woolley, 2020). Moreover, people might believe that humans should be responsible for processes and decisions of high relevance (Binns et al., 2018). At the same time, scholars have emphasized the importance of considering the degree of process automation along a continuum rather than comparing automated to human decisions, as done by most studies (Glikson & Woolley, 2020). Given AI-based systems' reliance on fixed variables, people might favor augmented processes, seeing human involvement as a counterbalance that ensures a deeper analysis of idiosyncratic information. By incorporating human involvement, the process seems less impersonal, meeting individuals' desire for closeness and respect while also allowing organizations to signal their appreciation for innovation and human capital (Langer & Landers, 2021). To our knowledge, Gonzalez et al. (2022) are the first to address these issues in the context of AI-based personnel selection. They considered differences in the selection stage (initial screening vs. final selection) and the selection approach (human vs. augmented vs. automated approach) and found that there are indeed differences in the evaluation of augmented and automated approaches in that applicants evaluate the former more positively and perceive it as more procedurally just. However, they did not find differences in the effects of the approach depending on the selection stage. In essence, initial evidence suggests that accounting for different contextual factors is crucial for testing the results' robustness and offering practical implications for developing and implementing AI-based selection procedures.

Theoretical Lens

Our theoretical lens is grounded in organizational justice theory. Conceptually, organizational justice typically comprises the dimensions of distributive, interpersonal, informational, and procedural justice (Colquitt, 2001). Procedural justice refers to individuals' assessment of the fairness of decision processes leading to outcomes which are important to the individual (Colquitt, 2001; Greenberg, 2003). That justice dimension is especially suitable to study applicants' perceptions of personnel selection (Gilliland, 1993; McCarthy et al., 2017). Additionally, we choose a procedural justice perspective to tie in with previous research on individuals' perceptions of AI-based procedures in organizational settings which differ from human-based processes (e.g., Jiang et al., 2022). Procedural justice perceptions are formed by individuals' perceptions of "voice" (i.e., the possibility of expressing one's own opinion), the perceived correctness of the decision, the perception of biases in the decision-making and the ethicality of the process (Colquitt, 2001; Leventhal, 1980). The importance of those perceptions and resulting procedural justice is indicated by the fair process effect (van den Bos, 2005; van den Bos et al., 1997), which shows individuals' reactions largely depend on the perception of procedural justice (van den Bos et al., 1997). Thus, while favorable outcomes are inherently valuable (Brockner & Wiesenfeld, 2005), individuals may react negatively if they perceive the decision-making process as unfair, even if the outcome is to their advantage.

Research Model

In the context of AI-based systems used in personnel selection, the decision-making itself is often perceived as a "black-box" by applicants (Lehmann et al., 2020). Thus, there is no possibility for voice during decision-makings nor to monitor the decision-making and to evaluate the correctness of the procedures. In this light, transparency regarding those procedures might be appropriate to increase individuals' possibilities to make sense of the processes and to increase procedural justice perceptions (Shin et al., 2022). Transparency is about the "perceived quality of intentionally shared information" (Schnackenberg & Tomlinson, 2016, p. 1788) and is commonly understood as a multidimensional construct (Lee et al., 2002; Schnackenberg & Tomlinson, 2016). We follow the conceptualization of Schnackenberg and Tomlinson (2016) and consider the three dimensions of disclosure, clarity, and accuracy. Disclosure is the perception that the right amount of information is shared in a timely manner. In particular, information which is received too late might have no value for information recipients. Similarly, huge amounts of information (i.e., information overload; Roetzel, 2019) is also reducing that information's perceived quality. Clarity is the perception that shared information is comprehensible to the information's receiver. This includes the way of presenting the information. Finally, accuracy is about the perceived correctness of shared information at the point of time of sharing (Schnackenberg & Tomlinson, 2016). Therefore, depending on information recipients' needs, perceptions of information quality differ between individuals (Albu & Flyverbom, 2019). In IS research, transparency is shown to foster positive outcomes such as trust (Nicolaou et al., 2013) and reduces negative perception such as uncertainties (Venkatesh et al., 2016). We hypothesize a similar effect of the individual transparency dimensions on procedural justice of AI-based selection processes. This is because providing information about the procedures and decision-rules enables applicants on the one hand to assess the whole process and to convince themselves that the selection process follows acceptable rules. On the other hand, the ability of organizations using AI-based personnel selection applications to provide high-quality information (i.e., right amount, clear, accurate) allows conclusions to be drawn about the ability to design and use fair AI-based systems for recruiting. Comparably, previous research showed in a sport-context that individuals' perceptions of transparency of technology-supported decision-makings increases their evaluation of the fairness of its usage and ultimately increases their positive attitude towards this system (Märtins et al., 2022). Compared to the sport-context, the consequences of AI-based decisions in personnel selection are even more serious (i.e., (not) staying in the process), therefore applicants might be even more interested in information concerning the decision-making. Thus, we propose Hypothesis (H)1:

H1: Applicants' perceptions of transparency in the form of a) disclosure, b) clarity and c) accuracy are positively related to their perceptions of procedural justice.

Research demonstrates that perceptions of procedural justice reliably predict individuals' reactions (Brockner & Wiesenfeld, 2005; Colquitt, 2001; Gilliland, 1993). The fair process effect, which has proven robust across diverse contexts and influences a wide range of outcomes, highlights the fundamental role of procedural justice (Greenberg, 2003). To better understand this role, various theoretical perspectives can be adopted. For instance, individuals infer their value from the treatment they receive during decision-making. If they feel that their input is adequately considered within the process, they feel more valued and perceive the process as fair. These perceptions of procedural justice ultimately improve their overall experience with the process, regardless of the decision outcome (Tyler & Lind, 1990; van den Bos, 2005). Procedural justice, however, gains particular importance in situations where decision outcomes are disfavoring (Brockner & Wiesenfeld, 2005). This is commonly observed in personnel selection where several applicants compete for a single vacant position. As a natural consequence, most applicants receive a rejection and thus an unfavorable decision outcome. In line with theory and prior research, we hypothesize that procedural justice is positively related to applicants' overall assessment of process quality.

H2: Applicants' perceptions of procedural justice are positively related to their evaluations of process quality.

To reduce the impact of unobserved effects, we control for age, gender, and education. Existing research on AI in decision-making demonstrates that these factors can significantly shape individuals' reactions. For instance, studies indicate that women tend to respond less favorably towards automated decision-making compared to men. Age seems to partially influence perceptions of AI-based systems, with older people being less convinced that automated decisions are free of bias (Araujo et al., 2020). Moreover, research suggests that higher education levels are linked to greater perceived control over system processes and outcomes, as those with more education better understand their functions (Langer & Landers, 2021). In the specific context of personnel selection, these results have been confirmed, showing that men and applicants with higher levels of education perceive AI-based personnel selection systems more positively than do their counterparts (Zhang & Yencha, 2022). The research model is presented in Figure 1.

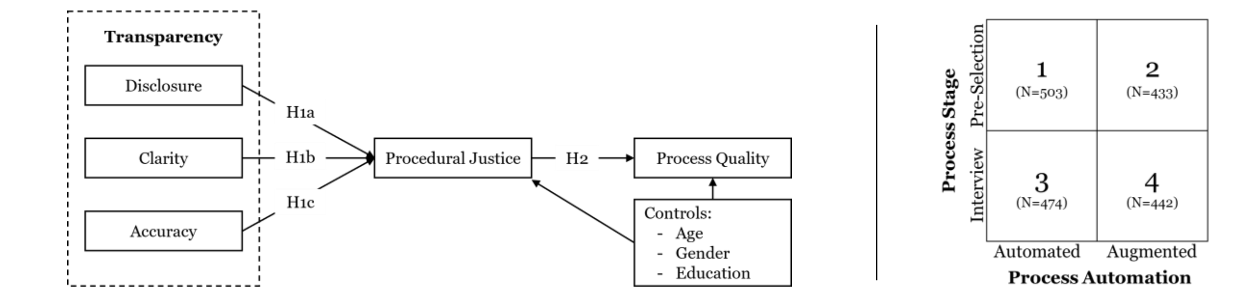


Figure 1. Proposed Research Model and Experimental Conditions

Methodology

Procedure and Manipulation

To analyze how the implementation of AI-based systems in the personnel selection process is evaluated, we applied a quasi-experimental, scenario-based survey approach. To simulate the perception of different selection situations, we implemented a 2 (degree of process automation: augmented process vs. automated process) × 2 (process stage: pre-selection vs. interview) full factorial survey design (see Figure 1). To create realistic, comprehensive, and immersive scenarios, we simulated a personnel selection process which we presented to participants. We conducted a pre-test to identify difficulties in question formulation or answer options, and feedback was incorporated accordingly. During data collection, participants first read information on study's purpose and data protection measures. After providing consent for participation and data recording, participants were asked to state their age, gender, education level, and employment status to ensure a representative sample. Then, we provided a definition of AI-based systems and randomly assigned each participant to one of the four scenarios. This between-subject design was chosen to prevent learning and carry-over effects (Atzmüller & Steiner, 2010). We provided a similar flow of information across all four scenarios. Participants were first presented with a fictitious email inviting them to the relevant selection step, which included information on how to proceed and details about the process. The emails were identical across all scenarios, except for the sections about the selection process stage concerned and about how the fictive decision would be taken (i.e., the degree of process automation). Subsequently, participants were shown mock-up representations of either the document uploading system or the video call tool to visually stimulate the immersion into the respective process stage.

In **scenario 1** (degree of process automation: automated, process stage: pre-selection), participants had to imagine themselves applying for a job and uploading their application documents to the company's recruitment tool. They were informed that the company preselects candidates using an AI-based system, employing image and character recognition technologies to analyze application documents. Although the specific functioning was not disclosed, participants learned that the system analyzes grades, academic skills, previous work experience, motivation, and keywords from the cover letter and past job references. Based on this analysis and after comparing with the job requirements and previous applicants, the AI-based system autonomously determines the candidate's suitability for the next selection stage. In **scenario 2** (degree of process automation: augmented, process stage: pre-selection), the stage remained the same; however, here, a human recruiter received a detailed ranking of all candidates created by an AI-based system, which was generated following the same procedure as in scenario 1. Based on this AI-curated ranking list, the human recruiter decides which applicant proceeds to the subsequent process stage. In **scenario 3** (degree of process automation: automated, process stage: interview), participants imagined being invited to a video-based job interview run by an AI-based system. They were informed that during the interview, the system poses questions and evaluates criteria to form a personality profile. These criteria include the content of the answers, speech rate, facial expressions, gestures, eye contact, and camera engagement. Though the specific functioning was not disclosed, participants were informed of the general aspects that the system evaluates. After forming the personality profile, the AI-based system compares it to the job requirements and profiles of past successful employees. Building on this, the AI-based system autonomously determines if the candidate moves on to the next stage. In **scenario 4** (degree of process automation: augmented, process stage: interview), the profile created by the AI-based system during the job interview is forwarded to a human recruiter to support decision-making. We consciously excluded information on the outcome of the decision to avoid con-founding results.

Data were collected via the respondi panel platform, specifically targeting German participants between the ages of 16 and 65. Members of this panel have volunteered to participate in scientific surveys and receive adequate monetary compensation for their invested time. After experiencing their assigned scenario, participants had to pass two manipulation checks considering the presented selection process stage and the degree of process autonomation. If they answered both questions correctly, they could continue with the subsequent questionnaire measuring their perceptions of the scenario on the scales presented in the following section. Finally, participants were asked to provide further demographic information. Overall, 2,020 individuals completed the survey (completion rate: 79.81%). Owing to three attention checks and four "knock-out" criteria regarding low response times, missing data, suspicious response patterns, and outliers, 168 participants were excluded from the analysis to ensure data quality (Leiner, 2019). This resulted in a final sample of 1,852 participants (48.9% female), representing the German workforce in terms of gender and age (Statista, 2020). The mean age was 41.98 years (SD = 13.87). The majority of participants have a professional educational background, with 57.5% holding degrees in the form of professional training or a bachelor's degree. A significant proportion of participants, 30.5%, have attained higher education levels such as a master's degree or higher. A comparatively small percentage of participants, 2.3%, have a low education level (no or low school education), and 9.7% of participants possess advanced qualifications. Participants took an average of 14 minutes (SD = 9:08) to complete the experiment.

Measurements

Established constructs were used to ensure sufficient validity. The items were linguistically adapted to the context of personnel selection and translated to German following a forward-backward procedure (Brislin, 1970). Transparency was measured on three dimensions, namely disclosure, clarity, and accuracy, which consist of four items each (Schnackenberg et al., 2021). We used the German validation of Hossiep et al. (2021). To examine procedural justice, we used a construct with five items by Elkins and Phillips (2000). The aforementioned constructs were evaluated using their original 5-point Likert scales, while process quality was measured using a construct with three items adapted from Wixom and Todd (2005) on the original 7-point Likert scale. Demographic controls were interval-scaled. After data collection, we tested the reliability and validity of constructs. The composite reliabilities (CR), Cronbach's alphas (CA), and average variance extracted (AVE) of all constructs were above their respective thresholds (CA ≥ 0.7; Cronbach, 1951; CR ≥ 0.7, AVE ≥ 0.5; Fornell & Larcker, 1981; Hair, 2014). Further, all factor loadings exceeded the threshold of 0.6 (Hair, 2014). Table 1 summarizes validity measures across all four scenarios.

Scenario 1: Pre-Selection / Automated					**Scenario 2: Pre-Selection / Augmented**				
Construct	Mean (SD)	CA	CR	AVE	Construct	Mean (SD)	CA	CR	AVE
(1) D	2.916 (0.967)	0.933	0.952	0.833	(1) D	2.915 (0.930)	0.930	0.950	0.827
(2) C	3.628 (0.788)	0.881	0.917	0.736	(2) C	3.668 (0.719)	0.862	0.905	0.704
(3) A	3.549 (0.684)	0.910	0.937	0.787	(3) A	3.588 (0.644)	0.906	0.934	0.781
(4) PJ	2.719 (1.004)	0.943	0.956	0.813	(4) PJ	2.840 (0.957)	0.935	0.951	0.795
(5) PQ	3.695 (1.490)	0.945	0.965	0.901	(5) PQ	3.834 (1.425)	0.942	0.963	0.897
Scenario 3: Interview / Automated					**Scenario 4: Interview / Augmented**				
Construct	Mean (SD)	CA	CR	AVE	Construct	Mean (SD)	CA	CR	AVE
(1) D	2.812 (0.936)	0.920	0.943	0.807	(1) D	2.775 (0.877)	0.916	0.941	0.799
(2) C	3.578 (0.763)	0.874	0.913	0.724	(2) C	3.559 (0.760)	0.874	0.912	0.722
(3) A	3.494 (0.726)	0.930	0.950	0.827	(3) A	3.484 (0.691)	0.923	0.946	0.813
(4) PJ	2.598 (0.963)	0.929	0.947	0.780	(4) PJ	2.587 (0.892)	0.928	0.946	0.777
(5) PQ	3.530 (1.502)	0.944	0.964	0.898	(5) PQ	3.464 (1.391)	0.930	0.956	0.877

Note. D = Disclosure; C = Clarity; A = Accuracy; PJ = Procedural Justice; PQ = Process Quality; SD = Standard Deviation; CA = Cronbach's Alpha; CR = Convergent Reliability; AVE = Average Variance Extracted.

Table 1. Descriptives, Reliability, and Validity of Measurement Instruments

The Fornell-Larcker criterion and the Heterotrait-Monotrait ratio were employed to assess discriminant validity (see Table 2). The Fornell-Larcker criterion demonstrated discriminant validity, as the square root of the AVE for each construct surpassed the correlation of the construct with any other construct (Fornell & Larcker, 1981). Furthermore, the Heterotrait-Monotrait ratios were found to be below the 0.9 threshold, supporting discriminant validity for the measurement models under examination (Henseler et al., 2015). Common method bias (CMB) may occur as both the independent and dependent variables were collected within the same survey for each of the four scenarios. To mitigate this, the items measuring the constructs were randomly ordered for the participants (Podsakoff et al., 2003). We employed Harman's single-factor test (Harman, 1967) based on principal-component analysis for all items of the five latent variables measured in the four scenarios. In Scenarios 1, 2, and 3, four factors were discerned with eigenvalues surpassing one, cumulatively representing 78.997% (scenario 1), 77.350% (scenario 2), and 77.371% (scenario 3) of the total variance. Of these, the primary factor accounted for 31.069%, 30.341%, and 29.731% respectively. Within scenario 4, three factors were identified, constituting 72.577% of the total variance, with the principal factor elucidating just 29.768%. Overall, Harman's single factor test and Kock's full collinearity approach (Kock, 2015) indicate that CMB is not a substantial issue in each of the four scenarios.

Scenario 1: Pre-Selection / Automated						**Scenario 2: Pre-Selection / Augmented**					
	Correlations / HTMT						Correlations / HTMT				
	(1)	(2)	(3)	(4)	(5)		(1)	(2)	(3)	(4)	(5)
(1) D	(0.913)	0.517	0.521	0.473	0.480	(1) D	(0.909)	0.520	0.441	0.437	0.457
(2) C	0.512	(0.858)	0.656	0.410	0.432	(2) C	0.510	(0.839)	0.641	0.381	0.411
(3) A	0.523	0.652	(0.887)	0.468	0.463	(3) A	0.443	0.637	(0.884)	0.440	0.449
(4) PJ	0.472	0.404	0.468	(0.902)	0.835	(4) PJ	0.436	0.370	0.439	(0.892)	0.818
(5) PQ	0.480	0.427	0.464	0.835	(0.949)	(5) PQ	0.457	0.396	0.450	0.818	(0.947)
Scenario 3: Interview / Automated						**Scenario 4: Interview / Augmented**					
	Correlations / HTMT						Correlations / HTMT				
	(1)	(2)	(3)	(4)	(5)		(1)	(2)	(3)	(4)	(5)
(1) D	(0.898)	0.481	0.485	0.442	0.450	(1) D	(0.894)	0.483	0.437	0.425	0.425
(2) C	0.470	(0.851)	0.667	0.390	0.394	(2) C	0.469	(0.849)	0.698	0.386	0.394
(3) A	0.485	0.664	(0.910)	0.454	0.472	(3) A	0.438	0.699	(0.902)	0.426	0.425
(4) PJ	0.442	0.383	0.455	(0.883)	0.799	(4) PJ	0.422	0.372	0.422	(0.881)	0.812
(5) PQ	0.450	0.385	0.472	0.796	(0.948)	(5) PQ	0.422	0.379	0.424	0.811	(0.937)

Note. D = Disclosure; C = Clarity; A = Accuracy; PJ = Procedural Justice; PQ = Process Quality; HTMT = Heterotrait-Monotrait Ratio of Correlations.

Table 2. Correlations and Discriminant Validity

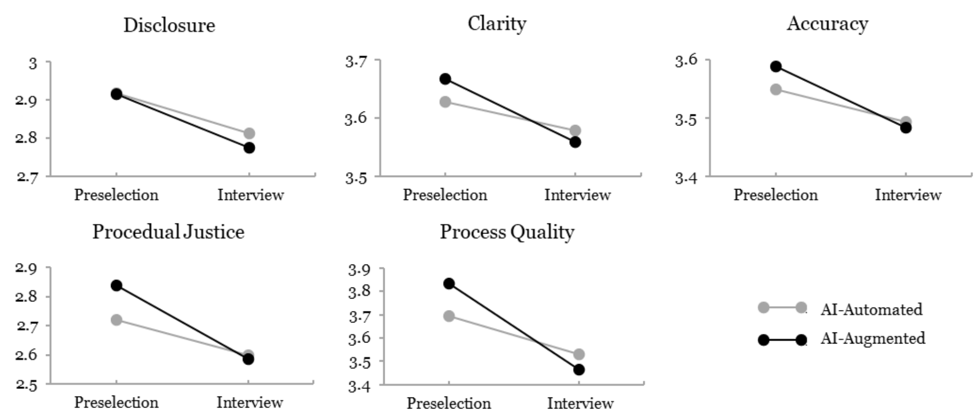
Data Analysis

Data analysis was carried out in three stages. First, a mean comparison across the four scenarios in perceived transparency (disclosure, clarity, and accuracy), procedural justice, and process quality was examined using independent-samples Welch's univariate ANOVA (Tomarken & Serlin, 1986). Addressing RQ1, the significance of the proposed relationships was assessed within each of the scenarios. We employed PLS-SEM using the SmartPLS software. PLS is extensively utilized in IS research (Ringle et al., 2012) and was favored over covariance-based SEM due to its lack of assumption of a normal distribution, its suitability for complex models, and the increased robustness offered by its bootstrapping method (Hair et al., 2016). SEMs were computed for all four scenarios, employing bias-corrected bootstrapping based on a bootstrap sample of 5,000. To address RQ2, pairwise MGA was conducted to examine whether there were significant differences between the path coefficients within the four scenarios (Cheah et al., 2023; Hair et al., 2016). The test for measurement invariance revealed no significant differences in the measurement models across the four scenarios, suggesting that potential discrepancies are not attributable to measurement error and that the MGA yields reliable results at the construct level (van de Schoot et al., 2012).

Results

Descriptive Statistics

The mean values of the latent variables from the proposed research model are presented in Figure 2. The results of the independent-samples Welch's univariate ANOVA provide initial evidence that the perception of the transparency dimension disclosure ($F(3, 1022.480) = 2.779$, $p = 0.040$, $\eta^2 = 0.004$) differs between the four scenarios, whereas for the transparency dimensions clarity ($F(3, 1022.839) = 1.959$, $p = 0.118$, $\eta^2 = 0.003$) and accuracy ($F(3, 1021.746) = 2.353$, $p = 0.071$, $\eta^2 = 0.004$) there are no indications of differences between the four scenarios. For procedural justice ($F(3, 1022.087) = 7.402$, $p < 0.001$, $\eta^2 = 0.011$) and process quality ($F(3, 3911.773) = 6.070$, $p < 0.001$, $\eta^2 = 0.009$), the ANOVA also provides evidence of differences between the scenarios.



Note. Disclosure, Clarity, Accuracy = measured on a 5-point Likert scale; Process Quality = measured on a 7-point Likert scale.

Figure 2. Mean Values by Process Stage and Degree of Process Automation

In order to examine specifically between which scenarios differences exist, pairwise independent-samples Welch's t-tests (Rasch et al., 2011) were conducted as part of a post-hoc analysis. Owing to the issue of multiple comparisons and the associated alpha error accumulation within t-tests performed, the Holm correction was applied (Holm, 1979). The results are summarized in Table 3. The results of the post-hoc analysis revealed that the perception of the transparency dimension disclosure does not show significant differences between any of the scenarios. Significant differences were identified for procedural justice and process quality between scenarios 2 and 3 and 2 and 4, respectively.

Scenario		Disclosure				Procedural Justice				Process Quality			
		Mdiff.	t	Cohen's d	p_{holm}	Mdiff.	t	Cohen's d	p_{holm}	Mdiff.	t	Cohen's d	p_{holm}
1	2	0.001	0.016	0.001	1.000	-0.121	-1.934	-0.127	0.145	-0.139	-1.459	-0.096	0.290
	3	0.103	1.735	0.111	0.331	0.121	1.976	0.126	0.145	0.165	1.774	0.114	0.229
	4	0.140	2.311	0.151	0.126	0.132	2.116	0.138	0.138	0.231	2.434	0.159	0.060
2	3	0.102	1.656	0.110	0.331	**0.242**	**3.810**	**0.253**	**<0.001**	**0.304**	**3.146**	**0.209**	**0.008**
	4	0.139	2.213	0.150	0.135	**0.253**	**3.916**	**0.265**	**<0.001**	**0.370**	**3.761**	**0.254**	**0.001**
3	4	0.037	0.598	0.040	1.000	0.011	0.174	0.012	0.862	0.066	0.683	0.045	0.495

Note. Welch's t-Test; Mdiff = Mean Difference; Bold numbers indicate significant results (p < 0.05).

Table 3. Results of Comparative Analysis

Measurement Model

Before we tested the proposed structural model, a confirmatory factor analysis (CFA) was performed for each of the four scenarios to test the fit of the measurement model with five latent variables and 20 items with theoretical expectations (Kline, 2016). CFA provides information on the construct validity and reliability of the measurement scales and indicates measurement errors that may affect the subsequent analysis using PLS-SEM (Hair et al., 2016; Kline, 2016). CFAs were performed using the R-based lavaan package (Rosseel, 2012). The measurement model had a good fit in all four scenarios, as χ^2/df ratios were below 5 (Dash & Paul, 2021), the comparative fit indices (CFI) and Tucker-Lewis indices (TLI) exceeded 0.9, and root mean square error of approximation (RMSEA) and standardized root mean square residual (SRMR) were lower than 0.08 (see Table 4; Hooper et al., 2008; Hu & Bentler, 1999; Kline, 2016).

Scenario	**n**	**χ^2**	**p**	**χ^2/df**	**CFI**	**TLI**	**RMSEA**	**SRMR**
1: Pre-Selection/Automated	503	409.505	<0.001	2.559	0.999	0.998	0.056	0.039
2: Pre-Selection/Augmented	433	356.802	<0.001	2.23	0.999	0.998	0.053	0.044
3: Interview/Automated	474	312.284	<0.001	1.952	0.999	0.999	0.045	0.035
4: Interview/Augmented	442	504.54	<0.001	3.153	0.997	0.997	0.070	0.052

Note. CFI = Comparative Fit Index; TLI = Tucker-Lewis Index; RMSEA = Root Mean Square Error of Approximation; SRMR = Standardized Root Mean Square Residual.

Table 4. Model Fit Indices

Structural Model

PLS-SEM was performed for each of the four scenarios individually to empirically test the proposed research model (see Table 5). The corresponding hypotheses were assessed based on the standardized regression coefficient (ß) considering the significance level of 5% ($p < 0.05$) in each scenario.

Hypothesis	**Scenario 1**		**Scenario 2**		**Scenario 3**		**Scenario 4**		Hypothesis Assessment
	ß	p	ß	p	ß	p	ß	p	
H1a: D → PJ	**0.293**	**<0.001**	**0.286**	**<0.001**	**0.275**	**<0.001**	**0.282**	**<0.001**	**Supported**
H1b: C → PJ	0.091	0.098	0.054	0.372	0.080	0.132	0.073	0.181	Rejected
H1c: A → PJ	**0.255**	**<0.001**	**0.279**	**<0.001**	**0.270**	**<0.001**	**0.253**	**<0.001**	**Supported**
H2: PJ → PQ	**0.835**	**<0.001**	**0.818**	**<0.001**	**0.799**	**<0.001**	**0.811**	**<0.001**	**Supported**
C: Gen → PJ	-0.042	0.322	-0.077	0.058	**-0.090**	**0.021**	**-0.090**	**0.035**	-
C: Gen → PQ	**0.073**	**0.007**	-0.009	0.805	0.049	0.083	**0.070**	**0.014**	-
C: Age → PJ	-0.068	0.084	0.028	0.562	-0.004	0.946	0.028	0.502	-
C: Age → PQ	0.030	0.255	-0.040	0.174	0.032	0.269	-0.007	0.759	-
C: Edu → PJ	0.025	0.564	-0.028	0.455	0.001	0.990	**-0.092**	**0.016**	-
C: Edu → PQ	**-0.055**	**0.025**	**-0.085**	**0.004**	**-0.065**	**0.025**	**-0.055**	**0.037**	-

Note. D = Disclosure; C = Clarity; A = Accuracy; PJ = Procedural Justice; PQ = Process Quality; Gen = Gender; Edu = Education; Bold Numbers indicate significant results (p < 0.05).

Table 5. Results of Structural Equation Model

H1a posited a positive relationship between *disclosure* and *procedural justice*. The results across all scenarios supported this hypothesis, as the regression coefficients for the relationship between *disclosure* and *procedural justice* were consistently positive and statistically significant ($p < 0.001$). H1b proposed a positive relationship between *clarity* and *procedural justice*. However, the effect of clarity on procedural justice was not statistically significant in any scenario ($p > 0.05$). Therefore, H1b was rejected. H1c suggested a positive relationship between *accuracy* and *procedural justice*. The results supported this hypothesis, as the effect of *accuracy* on *procedural justice* was positive and statistically significant across all scenarios ($p < 0.001$). H2 posited a positive relationship between *procedural justice* and *process quality*. The results supported this hypothesis, as the effect of *procedural justice* on *process quality* was positive and statistically significant across all scenarios ($p < 0.001$). Regarding control variables, no significant effect was found for age ($p > 0.05$). Gender had a significant negative effect on procedural justice in scenarios 3 and 4 ($p < 0.05$), and a significant positive effect on process quality in scenarios 1 and 4 ($p < 0.05$). As for education, the results showed a significant negative effect on procedural justice in scenario 4 ($p < 0.05$) and on process quality across all scenarios ($p < 0.05$). Evaluating the model in the context of the four scenarios, we found the data fit well for procedural justice, as indicated by R^2 values ranging from 0.250 to 0.291. The Stone-Geisser test indicated that the model has considerable predictive relevance in all four scenarios for procedural justice, with Q2 values ranging between 0.194 and 0.237 throughout the scenarios. Regarding process quality, R^2 values ranged from 0.637 to 0.696, indicating a good fit. The Stone-Geisser test showed that the model has a large predictive relevance in all four scenarios for process quality, as evidenced by Q2 values greater than 0.5 across all four scenarios (Hair et al., 2016).

Multigroup Analysis

To test whether the tested relationships differ between the four scenarios in terms of path coefficients, all possible combinations were tested pairwise. The results of the MGA are summarized in Table 6, providing the difference in path coefficients of each of the scenarios compared for each hypothesis, as well as the associated p-value. No significant difference between the scenarios was found in any of the path coefficients compared, except for the effect of gender on process quality in scenario 1.

Hypothesis	**1 vs. 2**		**1 vs. 3**		**1 vs. 4**		**2 vs. 3**		**2 vs. 4**		**3 vs. 4**	
	Diff.	p	Diff.	p	Diff.	p	Diff.	p	Diff.	p	Diff.	p
H1a: D → PJ	0.007	0.943	0.018	0.770	0.011	0.850	0.011	0.865	0.004	0.915	-0.007	0.949
H1b: C → PJ	0.037	0.645	0.011	0.898	0.018	0.864	-0.026	0.731	-0.019	0.791	0.007	0.946
H1c: A → PJ	-0.024	0.747	-0.015	0.882	0.002	0.941	0.009	0.881	0.026	0.717	0.017	0.826
H2: PJ → PQ	0.017	0.499	0.036	0.145	0.024	0.362	0.019	0.471	0.007	0.832	-0.012	0.658
C: Gen → PJ	0.038	0.526	0.048	0.395	0.048	0.394	0.013	0.850	0.013	0.855	0	0.991
C: Gen → PQ	**0.082**	**0.038**	0.024	0.494	0.003	0.928	-0.058	0.162	-0.079	0.058	-0.021	0.557
C: Age → PJ	-0.096	0.765	-0.064	0.249	-0.096	0.089	0.032	0.639	0	0.997	-0.032	0.615
C: Age → PQ	0.070	0.079	-0.002	0.975	0.037	0.320	-0.072	0.093	-0.033	0.479	0.039	0.335
C: Edu → PJ	0.053	0.354	0.024	0.664	0.117	0.058	-0.029	0.580	0.064	0.277	0.093	0.082
C: Edu → PQ	0.030	0.462	0.010	0.748	0	0.965	-0.020	0.696	-0.030	0.495	-0.010	0.790

Note. D = Disclosure; C = Clarity; A = Accuracy; PJ = Procedural Justice; PQ = Process Quality; Gen = Gender; Edu = Education; Diff = Difference; Bold numbers indicate significant results (p < 0.05).

Table 6. Results of Multigroup Analysis

Discussion and Implications

General Discussion of Results

The results of the ANOVAs and the post-hoc tests show that perceptions of the transparency do not differ between the four scenarios. We deliberately did not manipulate transparency between the scenarios, so that the comparison of the mean values of these perceptions can be seen as a robustness check of the results. It can be concluded that the differences in perceptions of the other variables are not due to a potential difference in transparency between scenarios. For perceptions of procedural justice and process quality, we find differences between some of the scenarios. This is in line with previous research indicating differences in applicants' perceptions resulting from the configuration of AI-based personnel selection (Gonzalez et al., 2019; Gonzalez et al., 2022). More specifically, we find significant differences for procedural justice and process quality between the augmented pre-selection (scenario 2) and both interview settings (scenarios 3 and 4). Augmented pre-selection is shown to have higher mean values compared to the other settings. This can be interpreted in a way that suggests that the limited (i.e., augmented) use of AI-based systems in pre-selection of applicants is perceived as more positive than the use of AI-based systems in later process steps (regardless of the degree of process automation). The preference for the use of AI-based systems in pre-selection over interviews is in line with the MABA-HABA framework (Glikson & Woolley, 2020). Since it is easier to quantify information in application documents than to create personality profiles based on speech, facial expressions, and gestures, the pre-selection stage can be viewed as a more mechanically driven decision-making task, while the interview is subject to greater subjective influence. This leads to a more positive evaluation of AI-based processes for document screening during pre-selection and less positive reactions for interviews. In addition to the task type, the stakes associated with the process step may also affect reactions in a similar way. Although personnel selection is fundamentally a high-stakes situation, pre-selection is only the first step in the application process, whereas the final hiring decision is made based on the interview decision. Consequently, the later step is characterized with higher stakes. Referent cognitions theory (Cropanzano & Folger, 1989) and relative deprivation theory (Crosby, 1976) provide a theoretical explanation of why the stakes can influence applicant reactions. They suggest that proximity to a desired outcome influences sensitivity to fairness perceptions, so the fairness of a procedure has a strong impact on those closer to the desired outcome (Gonzalez et al., 2022).

The results of PLS-SEM show for all four scenarios that perceptions of disclosure (H1a) and accuracy (H1c) are positively related to procedural justice with medium-sized effects varying between 0.253 and 0.293. In contrast, perceptions of clarity are not significantly related to procedural justice in any scenario, leading to the rejection of H1b. The rejection of this hypothesis can be explained by the premise that a certain degree of clarity must be present, but this is fulfilled in all four scenarios. This is indicated by the relatively high mean value of clarity in all scenarios (M = 3.559-3.668). It is also conceivable that participants are used to similar systems in other areas and that the system, and the information presented, are easy to understand. Referring to the MGA, there are no statistically significant differences in effect sizes between the four scenarios. This indicates that the effects are not dependent on the concrete design nor on the stage in which AI-based systems are used in personnel selection and thus a certain degree of generalizability is deductible.

Furthermore, the results of PLS-SEM support H2, which indicated a positive relationship between applicants' perceptions of procedural justice and their assessment of process quality. We find a strong effect in all scenarios, which varies between 0.799 to 0.835. The MGA shows that there are no statistically significant differences in effect sizes. Therefore, procedural justice is considered as a major antecedent of process quality. This also highlights the relevance of research on antecedents of procedural justice.

We find some effects of our control variables on procedural justice and process quality. Looking at procedural justice, gender affects applicants' perceptions in both interview settings. In both scenarios, we find that male applicants have slightly higher procedural justice perceptions. In addition, education is negatively related to procedural justice in scenario 4, with a small effect size. Process quality is influenced by gender in scenarios 1 and 4, indicating that female applicants evaluate the process quality to be higher; and we find a negative effect of education on process quality for all four settings, with small effect sizes. While the results related to gender are consistent with existing research (Langer & Landers, 2021; Zhang & Yencha, 2022), the results related to education are particularly surprising. Previous research suggests that education is associated with a higher sense of control, as individuals with higher levels of education tend to better understand the functioning of the systems on which the process is based (Langer & Landers, 2021). One possible explanation for the contradictory result is that individuals with higher levels of education generally aspire to higher positions or executive levels. In such positions, applicants expect a corresponding level of commitment from the organization, equivalent to the effort required to achieve the educational level. In the case of AI-based personnel selection, applicants may not feel sufficiently valued, leading to poorer perceptions and responses. However, as all effect sizes are rather small, especially in comparison to the hypothesized effects, it cannot be assumed that these demographic variables are the main cause for these findings. Nevertheless, it should be noted that there are influences resulting from the controls.

Theoretical Contributions

Our findings contribute to different research fields. First, building on related research, our results highlight the crucial role of procedural justice perceptions in shaping applicant reactions to personnel selection, thus adding to research on applicant reactions and connected theories, such as organizational justice theory. This effect was initially found in traditional, not technology-supported, selection processes (McCarthy et al., 2017; Truxillo et al., 2004) and was also shown in AI-supported settings (Acikgoz et al., 2020; Ötting & Maier, 2018). In this regard, our study replicates and supports previous research in the field of IS. We further add to the stream of literature on procedural justice in AI-based personnel selection by introducing process quality as a novel consequence of procedural justice. Applicants' evaluation of process quality is an important assessment of their experience during the selection process, particularly relevant in the competitive landscape for skilled employees. Therein, evaluations of process quality might serve as a cue for the overall quality of the hiring organization and for working conditions and could thus have negative impacts, even in positive outcomes in personnel selection for individual applicants (see fair process effect).

Second, the study leans on related research and examines four different configurations of AI-based personnel selection procedures. By considering scenarios differing in the process stage where AI-based systems are used, and in the degree of process automation, the study not only substantiates the robustness of the observed effects but also makes a significant contribution to the existing literature. Most previous studies in the context of personnel selection have focused on specific use cases of AI-based systems (e.g., video interviews or applicant screening), neglecting applicant reactions in different stages of the selection process. Additionally, we contribute to the demand for research on the use of AI-based systems for augmentation in organizational settings (Ötting & Maier, 2018). In doing so, we emphasize a more nuanced consideration of process automation (and human intervention possibilities) as a continuum rather than solely focusing on purely human or automated decisions. This approach allows for a better understanding of the nuances of blending human and AI-driven decision-making in personnel selection processes.

Lastly, we contribute to transparency research in the field of IS. Our findings underline the usefulness of a multidimensional transparency understanding. They show that transparency dimensions (disclosure, clarity, and accuracy) are individual perceptions having distinct effects on procedural justice. However, especially in the research field of AI-based decision-making, transparency is frequently studied unidimensionally, mainly focusing on the amount of shared information (comparable to the disclosure dimension) without acknowledging other perceptions that build individuals' perceptions of information quality. This might be due to the predominantly experimental approaches varying the level of available information (e.g., Langer et al., 2018; Newman et al., 2020; Wesche et al., 2022). We add to those valuable approaches by not varying the level of information provided but by measuring individuals' perceptions of information quality. We build on the multidimensional conceptualization by Schnackenberg and Tomlinson (2016), which has already been applied in other IS-related settings, such as individuals' use of healthcare technologies (Oldeweme et al., 2021) or the use of decision support systems in sports contexts (Märtins et al., 2022). By relying on such approaches, we demonstrate the utility of this multidimensional understanding of transparency in the context of AI-based technologies.

Practical Implications

In addition to its theoretical contributions, this study offers practical implications for implementing AI-based selection processes. Those are especially relevant given recent legislation, such as the Illinois Artificial Intelligence Video Interview Act or the European Data Protection Regulation, which oblige organizations to provide information to individuals who are subject to automated decisions (Goodman & Flaxman, 2017). Our findings emphasize the importance of applicants' perception of information quality, which significantly contributes to positive applicant reactions (i.e., procedural justice) and ultimately to process quality evaluation. Therefore, the design of information provision is decisive. Organizations need to ensure that an appropriate amount of information is provided in a timely manner (disclosure dimension of transparency). In addition, organizations need to foster perceptions of accuracy of shared information. To do so, it might be necessary to measure applicants' perceptions of information quality on a regular basis. This can be done quantitatively or based on interview data. Here, we recommend interviewing successful candidates, candidates being rejected as well as candidates not accepting an offer, as perceived information quality is subjective and might also be influenced by the process outcome.

Moreover, our findings can guide organizations' strategic considerations as to whether to delegate personnel selection decisions to AI-based systems and, if so, to what degree and in what form of implementation. First, the results show that the application of AI-based systems is evaluated more positively in earlier process steps and as a tool for supporting human recruiters' decisions rather than for automating the entire process. Organizations should, therefore, employ AI-based systems to streamline personnel selection that supports the recruiters' decisions in the early process stages to increase the quality of their application management in dealing with large numbers of applicants. Second, in view of the finding that the applicants' education negatively impacts their selection process evaluation, organizations should carefully assess the application of AI-based systems in personnel selection and tailor it to the specific requirements of each job vacancy. AI-based systems may be an appropriate choice for positions with low educational requirements; however, when filling positions with high educational demands, a more restrained approach to employing AI-based systems is advisable to avoid deterring potential candidates with advanced educational backgrounds and to prevent negative perceptions of the selection process.

Limitations and Further Research

Our study has some limitations that open avenues for future research. While the study offers large-scale evidence on applicant reactions to AI-based selection processes, the findings' generalizability may be somewhat constrained. One aspect is that our sample had a slightly higher educational level than the general population in Germany (Destatis, 2023). Also, factors such as Germany's unique cultural attributes, data protection regulations, and level of digitalization may render the results less transferable to different contexts. Moreover, methodological choices might have affected our results. First, the study was designed as a scenarios-based survey and thus did not allow participants to experience an actual personnel selection situation. Although we followed best practice recommendations for scenario-based studies (Aguinis &

Bradley, 2014) to maximize scenario realism and encourage participants to imagine the situation vividly, this approach might have influenced participants' evaluations. However, this approach offers significant advantages: It allows for the investigation of occurrences that are difficult to observe naturally (e.g., applicant reactions during the selection process) while ensuring high internal validity through better control of potential confounding factors (Aguinis & Bradley, 2014). We thus consider the methodology employed to be appropriate, but encourage future research to explore different approaches, such as field studies involving real job applicants. We also suggest exploring more immersive simulations like computer- or virtual reality-based scenarios for further insights. Second, we tested the hypothesized relationships across two varying degrees of process automation, demonstrating the generalizability of our findings. However, regarding the augmented process, there are several ways humans and AI-based systems can collaborate. For instance, organizations can employ AI-based systems to delegate communication to human recruiters and automate the remaining selection process, or utilize AI-based systems to consolidate judgments from multiple human recruiters and generate a decision based on their input (Gonzalez et al., 2022). Future research could replicate this study under different forms of augmentation to gather additional empirical evidence on the generalizability of the identified relationships. Another potential limitation of this study relates to the manipulation of process stages, specifically the equivalence of the conditions for pre-selection and job interview. While the scenarios are thoroughly described and balanced regarding the information included, they differ in the nature of the information being evaluated. Although this should not compromise the study's validity, it could possibly have resulted in more negative reactions during the interview scenario for introverted or shy participants, a situation that could not occur in the pre-selection process. Regarding control variables, we used only age, gender, and education. However, Gonzalez et al. (2022) highlighted the influence of applicants' AI familiarity on their reactions to AI-based decisions. Therefore, future research should include technology-specific controls, such as AI familiarity.

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