The Use of Artificial Intelligence Tools in Personnel Selection: A Systematic (Literature) Review

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Abstract

Artificial intelligence (AI) is a rapidly progressing technology impacting people's personal and work lives. In the workplace, AI supports various processes, such as automated job interviews, and thereby helps to improve an organization's effectiveness and efficiency. Yet, in personnel selection, we need to know more about how applicants perceive AI as organizations rely on this pool of potential employees. Therefore, this systematic review focuses on how applicants perceive the use of AI in the personnel selection process. To provide an overview of the current findings related to this topic, this review presents data from a sample of 19 peer-reviewed journal articles published between 2019 and 2023. Results show that although various applicants' perceptions (e.g., fairness perceptions) have been studied, the findings related to how AI is perceived are mixed. Furthermore, applicant's perceptions are understudied, and more research is needed to understand how the use of AI in the selection process is perceived. Therefore, this review can serve as a basis for future research to better understand how applicants perceive AI. The findings may also help organizations determine whether and if so, how to include AI in their selection process.

Keywords: artificial intelligence, personnel selection, recruitment, systematic review, perception

The Use of Artificial Intelligence Tools in Personnel Selection: A Systematic (Literature) Review

For centuries technology has played an important role in people's lives, from the invention of the wheel to steam power, electrification, the first computer, and the internet. Today, technology development is progressing rapidly, creating even more advanced tools every day. It is not only transforming our personal lives but also the way we work. The term *Industry 4.0* (Fourth Industrial Revolution) describes the changes that come with the use of technology, more specifically with digitalization and automation, in the workplace. Industry 4.0 enables organizations to implement emerging technologies, such as learning machines and self-decision-making systems, in almost every department (Oztemel & Gursev, 2018). Examples include flexible manufacturing lines and autonomous robots (Dalenogare et al., 2018; Menezes et al., 2019) that yield an advantage by saving costs and reducing errors. To achieve this, they depend on advanced technologies and automation as their core elements (Autodesk Inc., n.d.). In most applications, these core elements are supported by artificial intelligence (AI). Although AI's introduction to the broader workplace only started in the 2010s (Logyc, 2023), today, a world without it is difficult to imagine. Moreover, the influence of AI is predicted to increase over time (Howard, 2019).

One example of the increased application of AI in the workplace is within the Human Resources (HR) department (Budhwar et al., 2022). In HR, for example, AI is transforming processes in recruitment, development, and training (Shaw & Varghese, 2018). Due to its novelty (Nankervis et al., 2021), research on AI in this area has only occurred in recent years (Palos-Sánchez et al., 2022). The focus of the research is on understanding AI's potential effects on employees' well-being and work as well as its application in various HR functions (Howard, 2019). An example of the latter is the application of AI in personnel selection. AI is used by organizations for CV screening, video interviewing, and ranking of applicants, amongst others (Nugent & Scott-Parker, 2022). The use of AI saves time and costs, as well as improving the quality of the process (Karaboga & Vardarlier, 2021). However, the application of AI does not only affect the organization, but also the applicants as they are part of the selection process, and thus are affected by the outcome of AI application.

During the selection process applicants create an image of an organization based on their treatment during the process (Lievens & Chapman, 2019). They assess the receipt of "appropriate interpersonal treatment and timely information […] and whether the selection instruments are perceived to be face valid and procedurally fair" (Chapman et al., 2005, p. 929). As organizations face problems such as the shortage of skilled workers and the aging workforce, hiring qualified personnel becomes even more challenging and competitive. Consequently, personnel selection becomes more important, and organizations want to make a good first impression to attract future employees. Hence, making applicants' perceptions a key topic in research (Nikolaou, 2021). However, this topic does not seem to be fully explored yet, as there is little empirical research (Horodyski, 2023; Van Esch & Black, 2019). Awareness and understanding of the potential effects of AI, whether positive or negative, would help in selecting and designing AI tools that are perceived positively by applicants (Howard, 2019). In turn, applicant perceptions about the selection process can be managed to ensure that a positive image of the organization is created. Therefore, this systematic literature review aims to investigate the question; *How do applicants perceive the use of AI in selection?* by focusing on past and current literature on this topic.

In line with the recommendations of Boland et al. (2014), this systematic review summarizes the existing data by investigating the findings of several studies. It thereby contributes to combating the issue of replicability within the field of psychology (Siddaway et al., 2019). In turn, the collected data could be used as a basis for further research to better understand how applicants perceive AI. Moreover, it adds to the discussion of whether the use of AI in personnel selection is beneficial or disadvantageous. In turn, it also helps organizations determine whether to use AI and if so, how. It may also help organizations in designing a selection process that is perceived positively by applicants and assists in finding ideal candidates (Bauer et al., 2006).

Theoretical Background

Artificial Intelligence

AI is considered one of the most important modern-day innovations (Palos-Sánchez et al., 2022), although it is relatively new to the broader workplace (Nankervis et al., 2021). Generally, AI is an interdisciplinary subfield of computer science (Jin, 2020) and refers to "the ability of machines to exhibit human-like intelligence" (Bughin et al., 2017, p. 7). However, this is only one of the multiple definitions that exist (Palos-Sánchez et al., 2022), as the concept of AI has not yet been clearly defined and summons different understandings of what the term means (Wang, 2008).

To understand how and why AI is important today, it is helpful to look at its history. One of the first major milestones in the evolution of AI was Alan Turing's paper *Computing Machinery and Intelligence* (Turing, 1950) about intelligent machines and how to build and test them (Anyoha, 2017). Thereafter, AI started evolving in different waves (Jaakkola et al., 2019). Within the first wave (1950s), which focused on programming languages, John McCarthy introduced the term "artificial intelligence", marking the starting point of AI research. The second wave (1970-1980s) focused on expert systems, which are programs that utilize knowledge-based reasoning to solve complex problems. The third wave (1990s) focused on solving the mismatch between logical structures and computer architectures, which historically prevented innovation. Today (fourth wave), the focus is on the system's learning ability (Jaakkola et al., 2019).

This learning ability provides new application possibilities for AI and contributes to the fast progress in Industry 4.0. Without a system's ability to learn, Industry 4.0 would not be possible (Peres et al., 2020) as it depends on systems that can make decisions and adapt to new situations and tasks (e.g., flexible manufacturing system). For a system to carry out these tasks, it needs to be able to learn. This is achieved with the help of machine learning – a subfield, and core characteristic of AI (Lee, 2020).

Machine learning refers to "the learning process in which [a] machine can learn [on] its own without being programmed to do it in a certain way" (Rąb-Kettler & Lehnervp, 2019, p. 107). Therefore, it uses different techniques that "are inspired by our knowledge and understanding of human thinking, learning processes, and memory storage […]" (Lee, 2020, p. 67). This includes features such as an associative neural network for associative learning. The foundation of these techniques are algorithms (Mahesh, 2020). Algorithms are also the basis for the machine learning methods: supervised, unsupervised, and reinforcement learning (Lee, 2020). An example of the way a system can learn is through the use of examples. If given different examples, e.g., the names of shapes, a system learns to associate shapes with their names and vice versa (Lee, 2020). The ability to learn makes machine learning ideal for developing software for speech recognition and natural language processing (Jordan & Mitchell, 2015). Furthermore, a system based on machine learning is capable of pattern recognition, which in the context of recruitment and personnel selection is useful for improving the process of identifying suitable candidates (Hamilton & Davison, 2022).

There are many benefits, as well as potential risks resulting from the development of AI. Within the organizational context, for example, AI has the potential to help organizations manage resources more effectively to benefit both employees and the organization (Hamilton & Davison, 2022). An example is programs designed to train employees to maintain an end-use product of high quality. AI can identify the most effective program by comparing various data sets (Hamilton & Davison, 2022). Furthermore, AI can help improve an organization's efficiency by automating processes e.g., using robots and autonomous vehicles (Nankervis et al., 2021; Wamba-Taguimdje et al., 2020; PwC, 2019). More specifically, routine tasks such as packaging or sorting goods are ideally suited to automation (PwC, 2019). Despite the significant advantages that AI and machine learning have for growth and innovation, the weaknesses and dangers must also be acknowledged (Palos-Sánchez et al., 2022). Given AI developments, employees fear being replaced by robots and consequently losing their jobs (Vrontis et al., 2022). Furthermore, there are major concerns, particularly regarding the security of personal data (Jha et al., 2020), as computer systems can be hacked, and the obtained data can be sold. Moreover, there is a risk of AI deceptively integrating personal information into commercial data without the user sharing full personal details (Chen, 2020).

The Use of Artificial Intelligence in Personnel Selection

Recruitment is about ensuring the pool of applicants is big enough and that the applicants are suitably qualified for the role in order to select ideal candidates (Liang, 2020). Selection, on the other hand, refers to the process of collecting information to evaluate and select an applicant for a specific position (Liang, 2020). Therefore, these functions are considered an important area of Human Resource Management (HRM) (Singh & Finn, 2003). While distinct, recruitment and selection are terms often used synonymously (Searle, 2018). Singh and Finn (2003) argue that recruitment goes hand in hand with personnel selection as the two processes overlap (Ployhart et al., 2017). In this review, the term personnel selection will be used to consolidate both processes to cover a wider range of literature that encompasses both processes.

Personnel selection is the process of finding the most suitable candidate to fill a specific position, starting with analyzing the job and identifying requirements that an applicant needs to meet to be considered suitable (Salgado, 2017). An organization must first attract possible applicants to create a large pool of applicants (Nikolaou, 2021). This can be achieved through the posting of job advertisements, networking (Shiplacoff, 1999), and active (online) recruiting (e.g., via social media platforms). Thereafter, information about the applicant provided in their application is collected (Nikolaou, 2021). In this phase AI can make assumptions about the applicant's personality and suitability for work based on the application letter (Karaboga & Vardarlier, 2021). Next, it is determined whether the applicant meets the requirements, which involves procedures such as interviews and assessment centers (Salgado, 2017). AI can then help to create applicant ranking models and support during video interviews by interpreting facial expressions or tone of voice (Karaboga & Vardarlier, 2021). In sum, organizations can use AI at all steps of personnel selection (Jha et al., 2020) – from job descriptions, screening, and scheduling interviews to sending job offers and supporting pre-onboarding (Jha et al., 2020; Rąb-Kettler & Lehnervp, 2019). A more detailed but non-exhaustive overview of the application of AI in personnel selection can be found in Table 1.

Table 1

The Application of Artificial Intelligence in Personnel Selection

Process of personnel selection	Application of artificial intelligence
Requirement analysis	• Job description optimization software (Albert, 2019)
Attraction of applicants	• Targeted job advertising optimization (Albert, 2019) • Multi-database candidate sourcing (Albert, 2019) • Employer branding monitoring (Albert, 2019)
Screening of applications	• CV screening software (Albert, 2019) • AI-powered background checking (Albert, 2019)
Assessment of fulfillment of requirements	• Assessment of skill match for roles (Guenole & Feinzig, 2018) • Analysis of applicant's body language (Karaboga & Vardarlier, 2021) • Recognition of personality (Karaboga & Vardalier, 2021) • Creation of applicant ranking models (Karaboga & Vardalier, 2021) • AI-powered psychometric testing (Albert, 2019)

Integrating AI into the personnel selection process has advantages and disadvantages that should be considered (Vrontis et al., 2022). Primary avenues of research in personnel selection mainly focus on possible advantages and disadvantages for organizations (organization's perspective) and applicants (applicant's perspective) but also on the tools used in the process. From the organizational perspective, an important benefit is saving costs and time, as well as enhancing the quality of the process and the applicants (Karaboga & Vardarlier, 2021). Saving costs and time also apply to applicants. Asynchronous interviews, for example, enable applicants to conduct their job interview from home (Fernández-Martínez & Fernández, 2020). Furthermore, organizations can rule out biases (Jha et al., 2020). However, this still depends on the programmer of the applied software, as that person may have subconscious biases that could lead to in-built prejudices (Jha et al., 2020). This would lead to possible discrimination (e.g., regarding age, gender, and race) of applicants (Fernández-Martínez & Fernández, 2020). In addition, as AI exhibits human tasks, thereby replacing the human factor, applicants may perceive the reduced interaction between applicant and recruiter as disadvantageous (Konradt et al., 2013). The biggest concern by far, however, is the security of personal data (Jha et al., 2020). As organizations are likely to use third-party organizations to support the AI-based selection process, applicants' data is thus shared (Jha et al., 2020). This creates the possibility of personal data being leaked. This is a concern for both the organization and the applicant.

The Perception of Applicants

Applicant's perceptions in selection processes have been studied since the 1980s (e.g., Liden & Parsons, 1986). One of the first theoretical frameworks developed to describe those perceptions is Gilliland's (1993) model of applicants' reactions to employment selection systems. It is based on the construct of organizational justice (Greenberg, 1990) and focuses on the perceived fairness of selection systems. More specifically, it distinguishes between procedural (e.g., job relatedness, opportunity to perform) and distributive justice (e.g., equality, needs). Over the years, the model has been tested by several other researchers (e.g., Bertolino & Steiner, 2007; Konradt et al., 2013; Konradt et al., 2017; Schleicher et al., 2006), resulting in general support for the model (e.g., Bauer et al., 2006; Hausknecht et al., 2004; Schleicher et al., 2006).

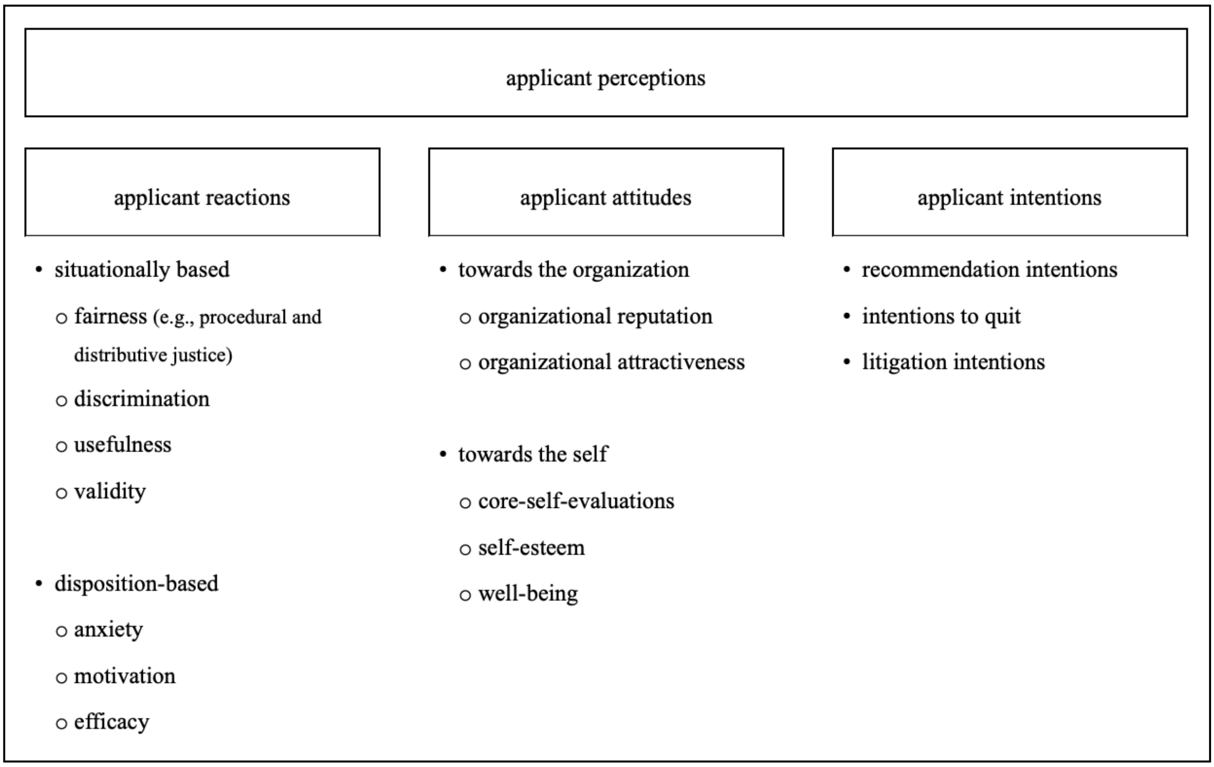
Furthermore, other theories contributing to the extension of Gilliand's (1993) model have been developed and tested. One of those theories is *The Applicant Attribution-Reaction Theory* (AART) by Ployhart and Harold (2004). It states that applicants' perceptions, such as fairness, self-perceptions, attitudes, and test perceptions, result from an attributional process. Hausknecht et al. (2004), on the other hand, proposed an updated theoretical model based on

Gilliland (1993) and Ryan and Ployhart (2000). According to this model, applicant perceptions are influenced by four groups of antecedents: (1) organizational context, (2) perceived procedure characteristics, (3) person characteristics, and (4) job characteristics. Applicant perceptions include procedural and distributive justice, text anxiety, test motivation, and attitudes toward tests and selection. In turn, they impact several outcomes of a selection process. For example, they may affect applicants' work attitudes, behavior, and performance after completing the selection process successfully (Gilliland, 1993). However, the perceptions not only impact the applicants themselves but also shape an organization's public image (Hülsheger & Anderson, 2009), thus making it an area of great research importance.

Generally, applicant perceptions describe applicants' attitudes and intentions regarding their participation in a hiring process (Hausknecht, 2013). As applicants' attitudes and intentions are predicted by applicant reactions (Hausknecht, 2013; McCarthy et al., 2017), applicant reactions are also relevant to the construct of applicant perceptions in this review. Applicant reactions "reflect how job candidates perceive and respond to selection tools […] on the basis of their application experience." (McCarthy et al., 2017, p. 1695). They can be categorized into situationally based and disposition-based reactions (McCarthy et al., 2017). Applicant attitudes refer to the evaluation of the organization (attitudes towards the organization) and the applicants' self (attitudes towards the self). This evaluation can range from positive to negative (American Psychological Association, 2018a). Applicant intentions, on the other hand, refer to a conscious decision (American Psychological Association, 2018b) that predicts behavior (Ajzen & Madden, 1986), such as terminating participation in the selection process. In short, applicants' reactions refer to a response, applicants' attitudes refer to an evaluation, and applicants' intentions refer to a behaviorpredicting decision. Figure 1 provides an overview of examples of the three sub-constructs of applicants' perceptions (applicants' attitudes, intentions, and reactions).

Figure 1

Examples of Applicants' Perceptions (Reactions, Attitudes, and Intentions)



Note. Categories and concepts based on McCarthy et al. (2017).

Based on the theoretical background described above, this review focuses on the following questions. In the context of personnel selection: (1) What perceptions of applicants have been studied, and what influence has AI use had on applicant perceptions? (2) What theoretical foundations are the studies on applicants' perceptions based on? (3) Based on the findings of the studies, what practical considerations are recommended for organizations regarding AI use?

Answering these questions will develop our understanding of how the use of AI in personnel selection is perceived by applicants. By providing an overview of research findings related to this topic researchers and practitioners can: (1) Use the findings of this review as a basis for future research (e.g., focusing on possibly understudied areas or expanding existing research on certain concepts) and (2) use the findings as a guideline for AI applications in organizations (e.g., whether and how to use AI in the selection process).

Methods

The following section describes how the systematic review (following the Preferred Reporting Items for Systematic reviews and Meta-Analyses (PRISMA; Page et al., 2021)) was conducted, including steps such as eligibility criteria, literature search, and data extraction. These steps are also part of the review protocol (Appendix A). It provides information related to the systematic review and therefore serves as a guideline and ensures that the settings and methods are defined before the review is conducted (Daniels, 2019).

Eligibility Criteria

Inclusion and exclusion criteria were defined based on the Population, Exposure, Comparator, Outcome, and Study (PECOS) framework (Daniels, 2019). Therefore, literature examining the general population (participants aged 18 or older) and focusing on applicants' perceptions of AI tools during the job application process were investigated. Furthermore, the focus of this review was on qualitative as well as quantitative studies, with no preference for research design. To ensure the inclusion of high-quality literature (Lomas et al., 2017), only peer-reviewed journal articles were included. These articles had to report their findings in the English language. Moreover, the articles had to be published (or in press) and accessible. Accessibility was met when articles were either accessible via the library of the University of Groningen or available as an open-access source, meaning that articles had to be accessible without producing any costs. An overview of the eligibility criteria is presented in Table B1 in the appendix.

Literature Search

As Daniels (2019) proposed, a dummy search was conducted to identify search terms. The final search terms are presented in Table 2.

Table 2

Search Terms Used for the Literature Search

No.	Search term
1	machine learning AND personnel selection AND attitude*
2	(artificial intelligence or ai or a.i.) AND personnel selection AND (perception* or reaction*)
3	(artificial intelligence or ai or a.i.) AND recruitment AND (perception* or reaction*)
4	algorithm AND assessment AND applicant*

The search terms were used to search various electronic databases – Web of Science, Scopus, and EBSCOhost (including PsycINFO and ERIC) – in December 2023 to identify articles that match the eligibility criteria. The database search was limited to the search within titles, abstracts, and keywords.

Selection, Screening, and Data Extraction

Following recommendations by Shamseer et al. (2015), firstly, titles and abstracts yielded by the search were screened against the inclusion criteria (Table B1) with the help of the screening tool Rayyan (Ouzzani et al., 2016). In the following step, the full-text reports were screened to determine whether they met the inclusion criteria (Table B1). This decision process was documented using an Excel spreadsheet. After this step, the data recommended by Daniels (2019) was extracted from the included studies, including bibliographic information and findings concerning the review question, and documented in an Excel spreadsheet. (For a detailed overview of the collected data items see Table B2.)

One reviewer conducted the selection and screening process from December 2023 to February 2024. Dr. Samantha Adams provided advisory support in the screening process by answering questions and clarifying uncertainties.

Results

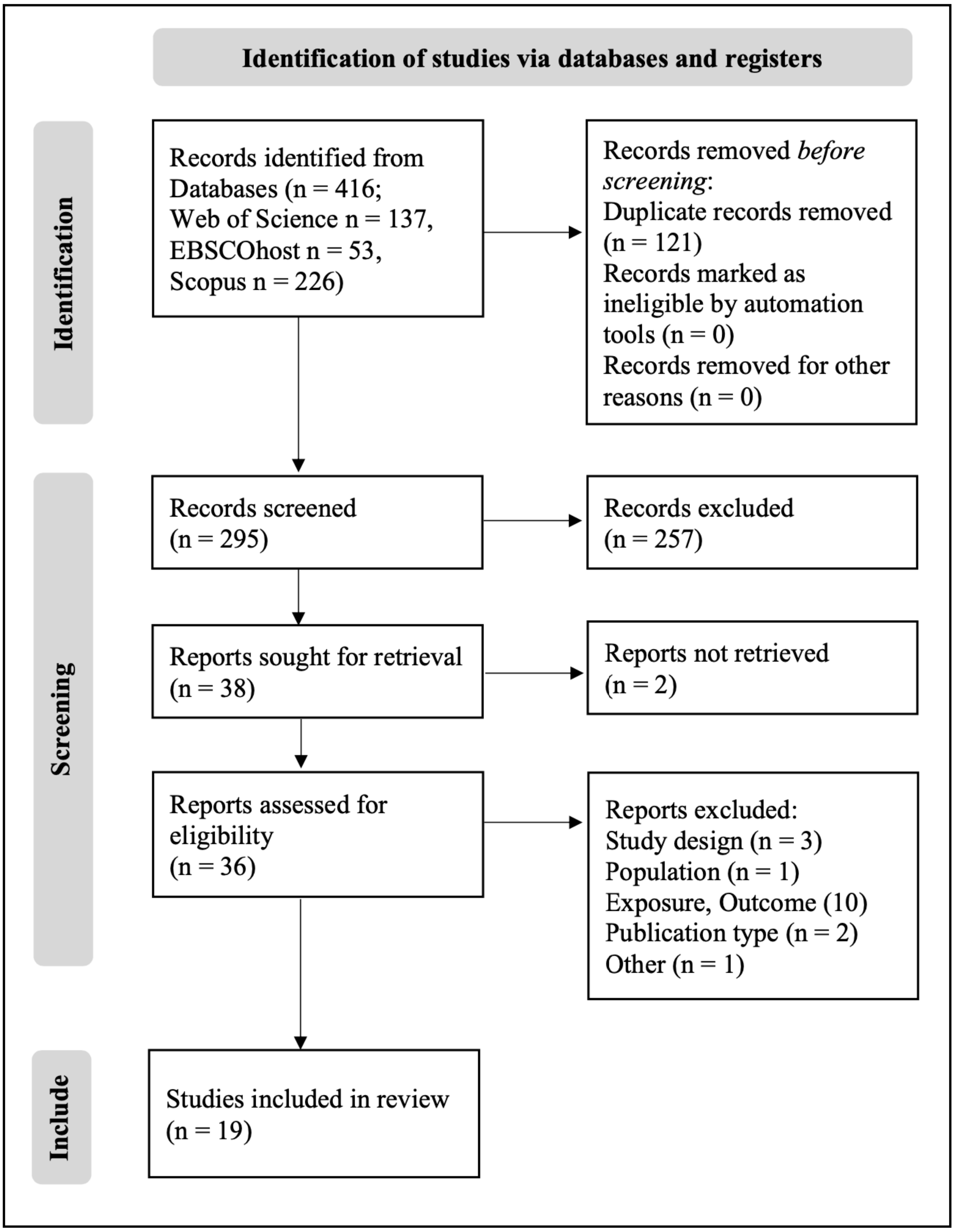
The following section focuses on the results of the systematic review. First, the results of the selection process are described, followed by reporting results referring to the individual research questions of interest.

Study Selection

The database search identified 416 records, from which 121 duplicates were removed. After screening the title and abstracts, 38 records remained. Two of them were not accessible via the library of the University of Groningen nor open access and were therefore excluded. The final screening of the full-text reports included 36 records. A further 17 records were excluded for the following reasons: (1) Records were other than journal articles (n = 2). (2) Records that did not fit the study design criteria (e.g., systematic reviews) were excluded (n = 3). (3) The population examined in the article was younger than 18 (n = 1). (4) Articles did not focus on the applicant's perceptions (n = 5). (5) Articles did not focus on the job application process (n = 4). Furthermore, one article failed to meet the inclusion criteria for both outcome and exposure (n = 1). Another article (n =1) included a job application process but investigated mortgage loan applications simultaneously and did not separate between these processes in the results section. In total, 19 records were included in the review. Table 3 provides an overview of the results of this selection process.

Table 3

PRISMA Flow Diagram Depicting Results of the Study Selection Process



Note. Diagram adapted from Page et al. (2021).

Study Characteristics

The included studies were published between 2019 and 2023. Most studies were quantitative studies (n = 15). Two studies used semi-structured interviews (Chen, 2023; Mirowska & Mesnet, 2022) and two further studies combined a quantitative and qualitative design (Leutner et al., 2023; Wesche & Sonderegger, 2021). As for the study population, the studies mainly focused on students and workers. Five studies generally mentioned recruiting participants from online platforms such as MTurk and Prolific Academic (Acikgoz et al., 2020; Horodyski, 2023; Noble et al., 2021; Van Esch & Black, 2019; Van Esch et al., 2019). Another study (Wesche & Sonderegger, 2021) recruited participants from German-speaking regions. The sample size differed depending on the type of study but was approximately N = 475 on average. Leutner et al. (2023), in particular, stands out with a sample size of N = 4,778. The least number of participants (N = 15) participated in the study by Chen (2023) due to the qualitative study design. For a detailed overview of the studies and their characteristics, see Table 4.

Table 4

Characteristics of the Included Studies

No.	Study	Study design	Study population	Sample size	Results summarized
1	Acikgoz et al. (2020)	Experimental design, quantitative study	MTurk workers (study 1), students (study 2)	298 (study 1), 225 (study 2)	• AI interviews were perceived more unfavorable in terms of procedural and interactional justice
2	Bedemariam & Wessel (2023)	Experimental design, quantitative study	Working adults resided in the USA	282	• Negative effect of AI on procedural fairness dimensions and general fairness reactions (when applicant is rejected by AI)
3	Chen (2023)	Semi-structured interviews, qualitative study	Managers, applicants, and recruiters	15	• Communication with a chatbot feels unnatural • Positive and negative responses regarding the use of AI tools
4	Duong & Pham Thi (2022)	Experimental design, quantitative study	Job-seekers (full-time students and students)	254	• Mediating and Moderating effect of self-efficacy on AI recruitment expected value and job seeker satisfaction

No.	Study	Study design	Study population	Sample size	Results summarized
4	Duong & Pham Thi (2022)				• Process flexibility of the recruitment is an important item for job-seeker
5	Horodyski (2023)	Experimental design, quantitative study	Participants from Profilic Academic	552	• Applicants perceive AI technology in hiring processes positively
6	Kandoth & Shekhar (2022)	Experimental design, quantitative study	(Indian) students	440	• Social influence had a direct and considerable beneficial impact on using an AI-assisted job application procedure and perceived trust • Personal trust partially mediated the relationship between social influence and intention to use AI
7	Köchling & Wehner (2023)	Experimental design, quantitative study	(German) working adults	200	• AI support without any additional information had a negative effect on fairness, emotional creepiness, and personableness perception

No.	Study	Study design	Study population	Sample size	Results summarized
7	Köchling & Wehner (2023)				• Use of AI and AI with additional written information reduces perceived fairness and personableness perception and increases emotional creepiness • AI with video information seems equal to a human evaluation in terms of fairness, personableness perception, and emotional creepiness
8	Köchling et al. (2023)	Experimental design, quantitative study	(German) working population	160	• AI-support in later stages of the selection process reduced the opportunity to perform and increased emotional creepiness

No.	Study	Study design	Study population	Sample size	Results summarized
8	Köchling et al. (2023)				• Relationship between AI-support and organizational attractiveness is mediated via opportunity to perform and emotional creepiness • No negative effect of AI-support in pre-selection on the opportunity to perform, emotional creepiness nor organizational attractiveness (if the hiring organization openly communicates the use of AI-support)
9	Langer et al. (2020)	Experimental design, quantitative study	(German) students	124	• Applicants perceived slightly lower opportunity to perform when they expected that their interview responses would be evaluated automatically

No.	Study	Study design	Study population	Sample size	Results summarized
10	Langer et al. (2021)	Experimental design, qualitative study	(German) students	124	• Process information may increase privacy concerns • Perceived fairness can be low when process information is presented but can increase when process justification is added to process information, which potentially has a positive impact on organizational attractiveness • Process information can induce negative emotional reactions • Providing limited information may not be detrimental • Presenting information does not necessarily increase perceived transparency

No.	Study	Study design	Study population	Sample size	Results summarized
11	Leutner et al. (2023)	Experimental design and open-ended questions, quantitative and qualitative design	Job applicants to graduate roles in a large consulting firm in Eastern Europe	4,778	• Game-based assessments deliver a favorable experience for most applicants
12	Mirowska & Mesnet (2022)	Semi-structured interviews, quantitative study	Adults, living and engaged in professional activities in France	33	• Participants raised concerns related to justice perceptions • Signaling effect of artificial intelligence evaluation use
13	Noble et al. (2021)	Experimental design, quantitative study	U.S. residents (MTurk workers)	360	• Algorithmic screening has negative and positive effects on justice perceptions (effects were mostly independent of the favorability of the screening procedure's outcome)
14	Schick & Fischer (2021)	Cross-sectional vignette study, quantitative study	Students	96	• Negative impact of AI complexity and intangibility on the assessment perception of knowledge, strengths and weaknesses

No.	Study	Study design	Study population	Sample size	Results summarized
14	Schick & Fischer (2021)				• High degree of reliability combined with a high AI complexity and high AI intangibility leads to a higher motivational assessment perception • Lower AI intangibility combined with a high AI complexity and low AI reliability leads to a higher motivational assessment perception • Combination of low AI complexity and high AI reliability leads to a higher motivation assessment perception independent of AI intangibility

No.	Study	Study design	Study population	Sample size	Results summarized
15	Suen et al. (2019)	Experimental design, quantitative study	(Chinese) members of a nonprofit HR organization, Recruiters	180 (+ 6 raters)	• Applicants are less favorable towards asynchronous interviews • Perceived procedural justice was not found to be lower for asynchronous video interview settings than for traditional synchronous video interview settings or for AI decision agent settings than for asynchronous video interview settings
16	Van Esch & Black (2019)	Cross-sectional design, quantitative study	Participants enlisted through a crowdsourcing platform	293	• Intrinsic rewards, fair treatment, and trendy had a significant and positive impact on the likelihood that applicants would engage in and complete an AI-enabled recruiting process

No.	Study	Study design	Study population	Sample size	Results summarized
17	Van Esch et al. (2019)	Cross-sectional design, quantitative study	Participants recruited through an online survey platform	532	• If applicants receive intrinsic benefits from using AI in the recruitment process, the likelihood of their application for a job that they know uses AI in the recruitment process increases • Attitudes towards organizations that use AI in the recruitment process significantly influences the likelihood that applicants will complete the application process • Novelty factor of using AI in the recruitment process mediates and positively influences job application likelihood

No.	Study	Study design	Study population	Sample size	Results summarized
18	Wang et al. (2021)	Experimental design, quantitative study	(Indian) students and employees	318	• AI tools contribute positively to increasing the number of quality applicant submissions (AI entrains a perception of a novel approach to job searching, AI is perceived to be able to interactively tailor the application experience to what the individual applicant expects and has to offer)
19	Wesche & Sonderegger (2021)	Experimental design and open-ended question, quantitative and qualitative study	Participants from German speaking regions (study 1 and 3), students in German speaking regions (study 2)	36 (study 1), 44 (study 2), 172 (study 3)	• Prospect of undergoing an AI-based, automated application screening procedure reduces participants' pre-process perception of organizational attractiveness and intention to apply

No.	Study	Study design	Study population	Sample size	Results summarized
19	Wesche & Sonderegger (2021)				• Fully automated application procedures are viewed negatively by job-seekers

Applicants' Perceptions

The following section describes the results yielded by the review in terms of the applicants' perceptions. Applicants' perceptions are composed of the applicants' intentions, attitudes, and reactions, as outlined in Figure 1 (above).

For an overview of the applicants' perceptions that have been studied, see Table C1.

Intentions

From the sample, eight studies focused on various applicant intentions including job pursuit intentions, litigation intentions, behavioral intentions, intention to use AI, intention to further proceed in the selection process, and job application likelihood (e.g., Acikgoz et al., 2020; Wesche & Sonderegger, 2021). Köchling and Wehner (2023) showed that regardless of whether AI is implemented with or without further explanation, it diminishes the intention to proceed further in the selection process. However, it was not associated with this intention if AI with video information was used (Köchling & Wehner, 2023). Job application likelihood of applicants is negatively affected when the screening process is AI-based (Wesche & Sonderegger, 2021). Non-automated and semi-automated procedures seem more favorable to applicants (Wesche & Sonderegger, 2021).

Attitudes

All the studies included in the review focused on attitudes toward the organization. More specifically, on organizational attractiveness, signal reactions, and organizational prestige. The focal point was therefore on organizational attractiveness, with a total of six studies (e.g., Langer et al., 2021; Horodyski, 2023) researching this topic. A few findings were similar to the ones regarding the applicants' intentions. In this case, organizational attractiveness was negatively affected both when using AI without further explanation and also when further explanation is provided (Köchling & Wehner, 2023; Wesche & Sonderegger, 2021). In addition, AI was not associated with increased organizational attractiveness if AI with video information was used (Köchling & Wehner, 2023). Contradictory to this finding, Langer et al. (2021) found that process information can impact organizational attractiveness positively. Generally, AI-based, automated application procedures seem to have a negative effect on the pre-process perception of applicants with respect to organizational attractiveness (Wesche & Sonderegger, 2021). On the contrary, Köchling et al. (2023) found a positive influence of AI support but only if the use of AI support is communicated openly. In turn, applicants' organizational attractiveness perception correlated positively with their perception of AI-enabled tools (Horodyski, 2023).

Additionally, Mirowska and Mesnet (2022) found both positive and negative signals. On the one hand, an organization is perceived as innovative and technologically advanced if it uses AI-based tools during the job interview. On the other hand, using AI is associated with possible problems with Human Resource processes (e.g., poor interview skills) and the perception that the organization does not value personal interaction.

Despite these contradictions, researchers agree that the impact of AI on organizational attractiveness depends on the information about AI that is provided to the applicants (e.g., Köchling et al., 2023; Langer et al., 2021; Wesche & Sonderegger, 2021).

Reactions

Following the categorization mentioned in Figure 1 (above), applicants' reactions can be either situationally based or disposition-based.

Situationally Based Reactions. Table 5 gives an overview of the situationally based applicant reactions that various studies focused on. While a lot of concepts have only been studied by one or two researchers, this section focuses on the constructs that have been investigated by several researchers.

Table 5

Situationally Based Applicant Reactions

No.	Applicant reaction
1	Expected value
2	Perceived usefulness
3	Perceived ease of use
4	(emotional) Creepiness
5	Privacy concerns
6	Favorability toward the interview process
7	Perceived interactivity
8	Trendy
9	Novelty
10	Fairness o Distributive justice o Interactional justice ▪ Interpersonal justice ➢ Propriety of questions ▪ Informational justice ➢ Openness o Procedural justice ▪ Job-relatedness ▪ Opportunity to perform ▪ Consistency ▪ Two-way communication ▪ Reconsideration opportunity ▪ Information known ▪ Transparency ▪ Feedback

Most studies (n = 16) focused on fairness perceptions, including distributive justice, interactional justice, and procedural justice. Generally, contradictory results can be found. On the one hand, AI can have a negative effect on fairness perceptions. Especially, when individuals are rejected by AI (Bedemariam & Wessel, 2023) or applicants receive no additional information about AI support (Köchling & Wehner, 2023). Although Langer et al. (2021) found low perceived fairness even when process information is presented to the applicants. Noble et al. (2021) also found algorithmic screening to reduce perceptions of treatment. Furthermore, due to the AI-supported selection process, specific groups (e.g., older applicants) could face discrimination (Wesche & Sonderegger, 2021).

On the other hand, AI can have positive effects on applicants' fairness perceptions as it allows for more objective and unbiased decision-making (Wesche & Sonderegger, 2021). Fair treatment also increases the likelihood of applicants engaging in and completing an AI-supported selection process (Van Esch & Black, 2019). Perceived fairness can furthermore be increased by adding process justification to process information (Langer et al., 2021).

Studies also provide evidence that an AI-supported selection process is not perceived as less fair compared to a traditional human-based selection process (Langer et al., 2020; Suen et al., 2019).

Interactional Justice. Generally, interactional justice is negatively impacted by using AI in the selection process (Acikgoz et al., 2020; Bedemariam & Wessel, 2023; Noble et al., 2021). Moreover, AI, for example, reduces perceptions of the propriety of questions, in other words, the selection process is perceived as less appropriate and free of prejudice (Noble et al., 2021). AI also lowers interpersonal interaction (Mirowska & Mesnet, 2022).

Procedural Justice. Ten studies reported findings related to procedural justice. The focus was on two constructs – job-relatedness (n = 5) and opportunity to perform (n = 6). In terms of job-relatedness, Acikgoz et al. (2020) and Langer et al. (2020) reported no effect of AI. Although Noble et al. (2021) found AI had a negative impact of AI on job relatedness. Two studies also stated that the job-related content could be increased (Chen, 2023; Leutner et al., 2023).

Opportunity to perform can be negatively affected by AI (Acikgoz et al., 2020; Bedemariam & Wessel, 2023; Langer et al., 2020; Noble et al., 2021), especially due to its complexity and intangibility (Schick & Fischer, 2021). Köchling et al. (2023) support this finding, although they differentiate between AI in preselection and at a later stage. According to their findings, the negative impact plays a role in later stages. In contrast, there is no negative influence on opportunity to perform in pre-selection (but only when using AI support is communicated openly). Also, accepted applicants perceived a greater chance to perform (Bedemariam & Wessel, 2023).

(Emotional) Creepiness. The concept is defined as an emotional reaction that is likely to be negative and uncomfortable and is caused by ambiguous perceptions towards, for example, a technology (Langer & König, 2018). According to Köchling et al. (2023), AI support did not increase emotional creepiness in preselection if it was communicated openly by the potential employer. However, emotional creepiness was increased in the later stages of the process. More generally, providing information about AI increased emotional creepiness (Köchling & Wehner, 2023; Langer et al., 2021). Furthermore, an AI-supported selection process is missing the human factor (Chen, 2023; Wesche & Sonderegger, 2021).

Disposition-Based Reactions. Studies focused on seven different disposition-based applicant reactions, namely satisfaction (n = 2), self-efficacy (n = 2), perceived trust (n = 2), personableness (n = 1), anxiety (n = 1), intrinsic rewards (n = 1), and technology use motivation (n =2).

Satisfaction. Two studies showed that applicants are satisfied with AI tools and an AI-supported assessment (Horodyski, 2023; Leutner et al., 2023).

Self-Efficacy. Applicants are worried about having too little knowledge and understanding of how a selection process supported by AI works, and how AI makes decisions (Wesche & Sonderegger, 2021). Self-efficacy partially moderates and mediates the relationship between the expected value of AI-supported selection processes and job seeker satisfaction (Duong & Pham Ti, 2022).

Perceived Trust. According to Kandoth and Shekhar (2022), perceived trust is positively impacted through social influence. In addition, perceived trust also partially mediates the relationship between social influence and an applicant's intention to use AI (Kandoth & Shekhar, 2022). Chen (2023) states that trustable AI is needed to build a trusting relationship between AI and humans.

Personableness. Köchling and Wehner (2023) found personableness to be perceived negatively by applicants when the selection process is supported by AI without any additional information. Personableness perceptions also decreased when written information about the potential benefits of AI was given. Providing video explanation did not influence personableness perceptions (Köchling & Wehner, 2023).

Anxiety. Anxiety was not found to affect the completion of job applications, although it predicts the job application likelihood (Van Esch & Black, 2019).

Intrinsic Rewards. If applicants receive intrinsic rewards from using AI in the recruitment process, their job application likelihood increases (Van Esch & Black, 2019).

Technology Use Motivation. Van Esch and Black (2019) and Wang et al. (2021) found a positive effect of technology use motivation on the novelty of AI and the job application likelihood.

Theoretical Foundation

Most studies (n = 14) referred to theories to explain what variables they focused on and why. Other studies did not refer to any theory (n = 4) or only provided a literature review (Duong & Pham Thi, 2022). The theories can be categorized into five categories: (1) technology acceptance theories, (2) theories related to behavior, (3) justice theories, (4) social theories, and (5) other theories. The emphasis was on the theories related to behavior as a total number of eight theories can be included in this category. Examples are the Theory of Planned Behavior and the Signaling Theory. The categories of technology acceptance theories (e.g., Technology Acceptance Model), justice theories (e.g., Gilliland's model), and social theories (e.g., Social Cognitive Theory) consist of three theories each.

Notably, Gilliland's (1993) model is most often referred to (n = 11) as well as the Organizational Justice Theory (n = 4). An overview of the studies and their theoretical foundations can be found in Table C2.

Practical Considerations

Out of the 19 studies included, two did not mention practical considerations (Kandoth & Shekhar, 2022; Leutner et al., 2023). Although most studies based their practical considerations on the specific setting they were looking at, similarities can be found. Authors agree on the importance of educating applicants on how and why AI is used when it is part of a selection process (n = 6; e.g., Bedemariam & Wessel, 2023; Langer et al., 2021). Noble et al. (2021) even recommend implementing communication channels for applicants to ask questions. Furthermore, including both AI and the human factor in the selection process is perceived as more favorable by applicants (n = 6; e.g., Acikgoz et al., 2020; Mirowska & Mesnet, 2022). Nevertheless, recruiters need to be aware that using AI tools could lead to unfair treatment of applicants (Köchling & Wehner, 2023).

Generally, choosing the right provider or AI tool is important (Van Esch & Black, 2019). However, CV screening and AI-based video and telephone interviews are examples of positively perceived AI tools (Köchling et al., 2023). To ensure good quality AI tools, algorithms should be used properly, and their development process should be transparent (Chen, 2023; Noble et al., 2021).

Moreover, there are contradictory implications based on the individual findings. For example, Köchling et al. (2023) recommend not to hide the usage of AI-based selection methods. Langer et al. (2021), on the other hand, say cutting down available information about AI-based automated systems might prevent negative application reactions. Another example is the humanizing of AI. According to Mirowska and Mesnet (2022), organizations should be careful about the degree to which AI is humanized. On the other hand, Bedemariam and Wessel (2023) recommend humanizing AI.

In summary, organizations should be cautious when implementing AI tools in the selection process as it might negatively affect an organization's attractiveness (Chen, 2023; Köchling & Wehner, 2023). If it is implemented, organizations should carefully consider the stage of the process in which AI is used (Wesche & Sonderegger, 2021). Organizations can also monitor if applicants drop out of the selection process when AI tools are applied (Köchling et al., 2023).

For a detailed overview of the practical considerations provided by each study, see Table C3.

Discussion

This systematic review focused on applicants' perceptions during an AI-based job selection process. It aimed to identify applicant perceptions studied by researchers. Additionally, it gives an overview of how applicants perceive the use of AI tools during the selection process. Moreover, theoretical foundations have been summarized. Lastly, the review focuses on practical considerations that can be derived for organizations based on the findings of the various researchers.

The study characteristics show that the included studies were published between 2019 and 2023, supporting the novelty of AI in the workplace (Nankervis et al., 2021). Furthermore, it shows that researchers only recently started researching the topic of applicant perceptions of AI-supported selection processes. As a limited scope of 19 studies was included in the systematic review, it is evident that there is relatively little empirical research on this topic (Horodyski, 2023; Van Esch & Black, 2019). Therefore, further research is required. To this end, this systematic review provides an overview of the current findings that may support future research.

Research Questions

Generally, the included studies adequately contributed to answering the identified research questions.

Applicants' Perceptions & Theoretical Foundations

With regard to the first research question relating to the influence of the use of AI on applicant perceptions, various applicant perceptions have been studied, which can be categorized into applicant intentions, attitudes, and reactions. However, the focus was on applicant reactions, including fairness perceptions. The majority of the studies have been devoted to this topic (e.g., Acikgoz et al., 2020; Bedemariam & Wessel, 2023; Langer et al., 2020), indicating that it is of great interest and importance. Surprisingly, the findings revealed contradictory results ranging from positive (e.g., Wesche & Sonderegger, 2021) to negative (e.g., Bedemariam & Wessel, 2023; Köchling & Wehner, 2023) perceptions of fairness when AI supports the selection process. This might be due to different experimental settings, measurements, and sample characteristics. However, interactional justice appears to be perceived negatively throughout the various studies focusing on this construct (Acikgoz et al., 2020; Bedemariam & Wessel, 2023; Noble et al., 2021). As fairness is an aspect of organizational justice, it is understandable that those studies used Gilliland's (1993) model or the concept of organizational justice (Greenberg, 1990) as a reference and starting point for their theoretical framework.

One of the biggest concerns regarding the use of AI is the security of personal data (Jha et al., 2020). The results of this review indicate that it is an area that still needs to be explored further, as only two studies in this sample (Langer et al., 2020; Langer et al., 2021) focused on privacy concerns. The same applies to discrimination. Although there is a concern about applicants facing discrimination due to the support of AI (Fernández-Martínez & Fernández, 2020), only one study (Wesche & Sonderegger, 2021) confirmed the possibility of specific groups facing discrimination.

Practical Considerations

Regarding research question three relating to practical considerations for organizations around AI use, findings are contradictory. However, there is some consensus regarding practical considerations. Studies recommend selection processes involving both AI and the human factor. A selection process solely using AI is perceived negatively. This may be due to the lack of human interaction, e.g., with a recruiter (Konradt et al., 2013). Applicants still prefer the human factor to be part of the process, even though they do not mind the incorporation of AI tools in general.

Theoretical Implications

One of the most popular frameworks for studying applicant reactions in the context of personnel selection is Gilliland's Model of Applicants' Reactions (1993). Unsurprisingly, the popularity of this model was reinforced by the results of this systematic review, as most of the included studies used the model as a theoretical foundation. Gilliland's (1993) model focuses on fairness perceptions, consequently, the studies emphasized the various sub-concepts of fairness (e.g., procedural justice).

However, applicants' perceptions are not only limited to fairness perceptions. Other perceptions, such as (emotional) creepiness, or privacy concerns need to be considered as well, as they contribute to applicants' perceptions in their entirety. In this regard, this systematic review also provides an overview of what other perceptions (within the categories of reactions, attitudes, and intentions) have been studied, but are also understudied. The aforementioned applicants' perceptions (classified within the reactions category) –

(emotional) creepiness and privacy concerns are just two examples of applicants' perceptions that are understudied. In the category of applicants' attitudes, signal reactions as well as organizational prestige are understudied. However, attitudes towards the self have not yet been studied at all. Examples in the category of applicants' intentions that are understudied include litigation intentions and intentions to further proceed in the selection process.

Although Gilliland's (1993) model has been extended, resulting in theories such as the AART (Ployhart & Harold, 2004), a general model regarding applicants' perceptions (including reactions, attitudes, and intentions) in personnel selection is yet to be developed and tested.

Managerial Implications

Although the question of whether the use of AI tools is beneficial in personnel selection cannot yet be answered conclusively, practitioners, such as recruiters and managers, are advised to consider the following when thinking about implementing and using AI in the selection process. Firstly, a selection process should not be solely based on AI. Including the human factor contributes positively to the perceived favorability of the selection process (e.g., Acikgoz et al., 2020; Mirowska & Mesnet, 2022). Therefore, a selection process should include both components: AI and the human factor. Secondly, applicants should be informed on how and why AI tools are used (e.g., Bedemariam & Wessel, 2023; Langer et al., 2021). This contributes to a positive perception of the selection process as applicants feel like the organization is being honest (Langer et al., 2021). Furthermore, transparency regarding the development of the algorithm used as a basis for the AI tool is recommended (Chen, 2023; Noble et al., 2021). In doing so, applicants can understand how the algorithm is composed and whether it may contain possible unconscious biases (Miller et al., 2018). Thirdly, constantly evaluating an AI-supported selection process helps to detect negative applicant perceptions towards applied AI tools (Koidl, 2024). In this way, the AI tools can either be adjusted or completely removed from the process to prevent further negative effects. Lastly, it is important to train HR employees who are in charge of designing, implementing, and evaluating the selection process for using AI tools (Koidl, 2024). Training not only creates awareness but also an understanding of the possible effects of AI, and thus how applicants might be affected by and feel about AI.

Limitations

Limitations of the Systematic Review

Although this review gives an overview of the current findings in the research of applicants' perceptions regarding the use of AI, its limitations must be acknowledged when interpreting the results. The fact that the review was conducted by only one researcher may have resulted in biases and decreased objectivity (Shamseer et al., 2015). To counteract biases and objectivity issues, support from an experienced researcher was provided. Additionally, a review protocol was used to plan and structure the review (Shamseer et al., 2015). Furthermore, using the screening tool Rayyan (Ouzzani et al., 2016) helped keep the error rate low. For future research, systematic review software, such as DistillerSR (DistillerSR, 2023) could also help to automate the process and limit possible mistakes. Secondly, only accessible (open access and free of charge) articles were included in this review. The results may have differed if the inclusion criteria had been extended to fee-based articles as well. However, it is likely the number of studies regarding applicants' perceptions behind this paywall is small.

Limitations of the Included Studies

The samples of studies mostly consisted of students and workers. Often, they participated in scenario-based studies, but not in real-life application processes. This may be due to the fact that laboratory experiments are easier to conduct and take place in a controlled setting. Then again, although there are various AI tools available, HR employees may not implement AI tools, because only a minority of HR employees acknowledge the value of AI (Bolton, 2018). A consequence is that research on AI-based selection processes conducted in the *real* world are scarce. There is also the possibility that the results could differ if data were collected in an actual AI-supported selection process. Studies conducted in a laboratory create an artificial environment. Although researchers try to design a realistic setting (e.g., using scenario-based experiments), it still does not reflect a real-life scenario. Factors such as location, equipment, and people present differ. Furthermore, if participants take part in a hypothetical application process, they may not take the task at hand as seriously as they would if they were applying for an actual job. Additionally, a real-life scenario tends to be more stressful and meaningful to the applicants as they, for example, need the job for monetary reasons or the job enables personal development or a step forward in one's career. Given that most studies used scenario-based experimental settings, shifting the focus to field studies might help to collect more representative data. Nevertheless, the results of this review indicate a trend helping to understand what to pay attention to when designing and conducting an AI-based selection process.

Future Research

Based on the findings of this review, the following avenues for future research in the context of AI-supported tools in selection processes are indicated. Firstly, there is a variety of AI tools available. Expanding research on this topic would create a detailed picture of which tools applicants perceive positively. Secondly, evaluating which of those tools would work best in each phase of the selection process (e.g., collection of applicant information, and assessment) would allow for creating a more positive experience for the applicant, as one tool might be more suitable than another. Of course, there will still be individual differences, but the goal should be to find the most positively perceived tool(s). Thirdly, most studies are scenario-based studies. Although they mimic the setting of a real-life event, it is an artificial situation. Collecting data from real-life settings would enable results to reflect reality. Building on that, the focus would also shift more towards job applicants instead of students. Lastly, focusing on replicating existing results contributes to expanding the available literature on this topic. Thereby, it might solve the problem of contradictory findings. Coherent results would improve the application of AI tools in organizations. Furthermore, it would create a clearer picture as to what extent AI tools are perceived positively or negatively. As only a limited amount of literature on this topic is currently available (Pan et al., 2022), more research is needed. However, this poses a challenge, as the development of AI tools is progressing rapidly, and hence may outpace the current rate of research.

Conclusion

Although “AI is still in its infancy” (Ade-Ibijola & Okonkwo, p. 104), it has a great impact on our daily lives and workplaces. This systematic review sought to provide an overview of the current findings related to the question of how applicants perceive the use of AI in the selection process. The review indicates that the results in this research area are inconclusive in many ways. AI could both positively and negatively impact applicants’ perceptions. This depends on the construct of perception (reaction, attitude, or intention) being studied and the AI tool being applied. However, most researchers agree on involving both AI as well as the human factor in the process to create positive applicant perceptions. Therefore, organizations should consider using AI carefully, and desist from a fully automated selection process. Nevertheless, more research is needed to solve the problem of inconclusiveness and to better understand applicant perceptions.

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*Denotes studies included in the literature review.

Appendix A

Review Protocol (Daniels, 2019; Shamseer, 2015)

Introduction

Background

The influence of Artificial Intelligence (AI) is touching different parts of society, thereby becoming an influential innovation (Palos-Sánchez et al., 2022). Even though it has multiple definitions, according to Bughin et al. (2017), the term generally refers to the ability of machines to exhibit human-like intelligence. This new technology is also being applied in the organizational context. Although it is relatively new to the broader workplace (Nankervis et al., 2021), it has the potential to help companies manage resources that benefit both employees and the firm more effectively (Hamilton & Davison, 2022). Nevertheless, there are major concerns, particularly the security of personal data (Jha et al., 2020). In the area of Human Resource management AI can be used to accelerate processes, such as personnel selection. Here AI can be applied to recruit and select the right people for a vacant job position faster (Guenole & Feinzig, 2018) than humans. Generally, it can be used at all steps of the process of recruitment and selection (Jha et al., 2020).

Selection "is the process of gathering information for the purpose of evaluating and deciding who should be employed in particular jobs" (Liang, 2020, p. 153). AI can be used in various parts of the process, starting with its ability to interpret the applicant's personality and convenience for work from an application letter (Karaboga & Vardarlier, 2021). In the further course of the process, AI can help create applicant ranking models and support during video interviews by interpreting facial expressions or tone of voice (Karaboga & Vardarlier, 2021).

Generally, the two primary avenues of research in personnel selection mainly focus on possible advantages and disadvantages for companies (organization's perspective) and applicants (applicant's perspective) regarding the process itself, but also on the tools that are being used in the process. Applicant's perspectives, also termed *applicant perception*, describes applicants' attitudes and intentions regarding participation in a hiring process (Hausknecht, 2013). Focusing on this aspect is of great importance not only because applicants' perception shapes the public image of an organization (Hülsheger & Anderson, 2009). It may also affect applicants' work attitudes, behavior, and performance after completing the selection process successfully (Gilliland, 1993).

As the topic of AI in the context of personnel selection is rather new, research has mostly occurred in recent years (Palos-Sánchez et al., 2022). Therefore, the proposed study aims to provide an overview of the current literature and research related to this topic. More specifically, the proposed systematic (literature) review focuses on the question of *How the use of AI in personnel selection is being perceived by applicants* by investigating the findings of several studies (Boland et al., 2014). Thereby, the review contributes to the issue of replicability within the field of psychology (Siddaway et al., 2019) and provides a summary of the existing data which could, in turn, be used for further research.

Objectives

The objective of this study is to systematically review the literature about the perception of the use of artificial intelligence (AI) in personnel selection by applicants. To this end, the proposed systematic literature review will answer the following question: How is the use of AI in personnel selection being perceived by applicants?

Methods

Eligibility Criteria

Studies will be selected according to the criteria outlined below.

Inclusion Criteria

Drawing from the PECOS framework studies matching the following criteria will be included:

- population: studies examining the general population (adults, 18 years or older)
- exposure and outcome: applicants' perception (including attitudes, intentions, and reactions such as job relatedness, face validity, procedural justice, and distributive justice) of the use of AI during the (job) application process
- study designs: qualitative and quantitative studies with any research design
- publication type: journal article
- language: articles reported in the English language
- published articles (or in press)
- accessible articles (accessible = available (free) via uni account or open access (e.g., research gate))
- peer-reviewed articles

Exclusion Criteria

- population, exposure and outcome
  - studies not examining the general population in the context of AI supported (job) application processes
  - studies not focusing on the perception of applicants (reactions, intentions, and attitudes)
  - studies focusing on individual differences (e.g., personality) in the context of AI supported (job) application processes
- study design: systematic review
- publication type: publications other than journal articles
- language: articles reported in languages other than English

- unpublished articles
- articles that are not accessible (via uni or open source)
- non peer-reviewed articles
- grey literature

Information Sources

The following electronic databases will be searched: (1) EBSCOhost (including PsycInfo and ERIC), (2) Web of Science, and (3) Scopus.

Search Strategy for Identification of Studies

The search terms (keywords) will be the following:

- machine learning AND personnel selection AND attitude*
- (artificial intelligence or ai or a.i.) AND personnel selection AND (perception* or reaction*)
- (artificial intelligence or ai or a.i.) AND recruitment AND (perception* or reaction*)
- algorithm AND assessment AND applicant*

Study Records

Data Management

The reference management software *EndNote* as well as an excel spreadsheet will be used to manage records and data throughout the review. Furthermore, the screening tool *Rayyan* will be used.

Selection Process

Firstly, titles and abstracts yielded by the search will be screened against the inclusion criteria. Full reports for all titles that appear to meet the inclusion criteria or where there is any uncertainty will be obtained. Then the full-text reports will be screened and decided whether these meet the inclusion criteria.

Data Collection Process

In order to collect data single extraction will be employed.

Data Items

The following data will be extracted from the included studies:

- bibliographic information (e.g., author(s), title of publication, year of publication, place of publication, volume number, issue, page number(s), publisher)
- information on where the study was conducted
- study population, size and characteristics of the sample
- hypotheses and theories used
- independent variables
- dependent variable(s)
- mediator(s)
- moderator(s)
- control variable(s)
- how the key variables were measured
- study design
- findings in relation to the review question (including effect sizes, significance for quantitative studies, any features relevant to the quality of the study (e.g., attrition rates, confounding, inadequacies in analyses)
- research context

Outcomes

Studies are included if they measured the applicants' perception of the use of AI during the application process.

Data synthesis

The data will be synthesised in a systematic review.

Appendix B

Eligibility Criteria and Data Items

Table B1

Overview of the Eligibility Criteria

	Inclusion criteria	Exclusion criteria
Population	• General population (participants aged 18 and older)	• Participants younger than 18 years
Exposure	• (job) application process with the use of AI tools	• Other applications processes than job application process with the use of AI tools
Outcome	• Applicant's perceptions	• Individual differences (e.g., personality)
Study design	• Qualitative studies • Quantitative studies	• Systematic review
Research design	• Any	
Publication type	• Journal article	• Other than journal articles
Language	• English	• Any other language than English
Other	• Published articles (or in press) • Peer-reviewed articles • Accessible via library of the University of Groningen or open access	• Unpublished articles • Non-peer-reviewed articles • Not accessible via library of the University of Groningen or open access • Grey literature

Table B2

Data Items

No.	Data item
1	Bibliographic information
2	Information on where the study was conducted
3	Study population, size, and characteristics of the sample
4	Hypotheses and theories used
5	Independent variables
6	Dependent variables
7	Mediators
8	Moderators
9	Control variables
10	Measurement of key variables
11	Study design
12	Findings in relation to the review question
13	Research context

Note. Data based on Daniels (2019).

Appendix C

Studied Applicants' Perceptions, Theoretical Foundations, and Practical Considerations

Table C1

Studied Applicants' Perceptions

No.	Study	Applicants' perceptions	Type of variable
1	Acikgoz et al. (2020)	Organizational attraction, job pursuit intentions, litigation intentions	Dependent variable
		Procedural justice perceptions (job-relatedness, chance to perform, consistency, reconsideration opportunity), interactional justice perceptions (openness, information known, two-way communication, treatment)	Mediator
2	Bedemariam & Wessel (2023)	Fairness, procedural justice (opportunity to perform, reconsideration opportunity, job-relatedness, information known, feedback), interactional justice (e.g., fair treatment)	Dependent variable
3	Chen (2023)	Attitudes (creepiness, job-relatedness, perceived ease of use, intention to use AI, trust)	Dependent variable
4	Duong & Pham Thi (2022)	Perception of AI recruitment expected value	Independent variable
		Job seeker satisfaction	Dependent variable
		Self-efficacy	Mediator/moderator
5	Horodyski (2023)	Perceived usefulness, perceived ease of use, satisfaction	Independent variable
		Behavioral intention, organizational attractiveness	Dependent variable
6	Kandoth & Shekhar (2022)	Intention to use AI	Dependent variable

No.	Study	Applicants‘ perceptions	Type of variable
		Perceived trust	Mediator
7	Köchling & Wehner (2023)	Organizational attractiveness, intention to further proceed in the selection process	Dependent variable
		Fairness, emotional creepiness, personableness perception	Mediator
8	Köchling et al. (2023)	Organizational attractiveness, opportunity to perform, emotional creepiness	Dependent variable
		Opportunity to perform, emotional creepiness	Mediator
9	Langer et al. (2020)	Opportunity to perform, fairness, privacy concerns, job relatedness	Dependent variable
10	Langer et al. (2021)	Organizational attractiveness, transparency, fairness, creepiness, privacy concerns	Dependent variable
		Creepiness, privacy concerns, transparency, fairness	Mediator
11	Leutner et al. (2023)	Overall satisfaction, ease of use, relevance	Dependent variable
12	Mirowska & Mesnet (2022)	Justice (distributive, procedural, informational, interpersonal), signal reactions (positive, negative)	Dependent variable
13	Noble et al. (2021)	Procedural justice (job relatedness-predictive, job relatedness-content), interpersonal justice (opportunity to perform, reconsideration opportunity, consistency, treatment, two-way communication, propriety of questions)	Dependent variable
14	Schick & Fischer (2021)	Perception of assessment quality (opportunity to perform regarding knowledge, motivation, strengths and weaknesses)	Dependent variable
15	Suen et al. (2019)	Applicant favorability towards the interview process, applicant perceived fairness	Dependent variable

No.	Study	Applicants' perceptions	Type of variable
16	Van Esch & Black (2019)	Intrinsic rewards, fair treatment, trendy	Independent variable
17	Van Esch et al. (2019)	Technology use motivation	Independent variable
		Job application likelihood	Dependent variable
		Attitude towards the organization, anxiety, novelty of activity	Moderator
18	Wang et al. (2021)	Technology use motivation	Independent variable
		Job application likelihood	Dependent variable
		Attitude towards the organization, perceived interactivity	Moderator
		AI novelty	Mediator
19	Wesche & Sonderegger (2021)	Intention to apply, organizational attractiveness, organizational prestige, fairness, expected (procedural) justice	Dependent variable

Table C2

Theoretical Foundations

No.	Study	Theories used
1	Acikgoz et al. (2020)	Applicant reactions models (e.g., McCarthy et al., 2017; Gilliland's model, 1993), signaling theory, fairness heuristic theory
2	Bedemariam & Wessel (2023)	Organizational justice theory, Gilliland's model (1993), signaling theory, fairness heuristic theory
3	Chen (2023)	(explanation of concepts but no explicit mentioning of theories)
4	Duong & Pham Thi (2022)	(theoretical background is built on literature review about research in synchronous and asynchronous interviews)
5	Horodyski (2023)	Applicant reactions models (e.g., McCarthy, 2017), technology acceptance model (TAM; Davis, 1989), theory of planned behavior (TPB; Ajzen, 1985), unified theory of acceptance and use of technology acceptance (UTAUT; Venkatesh et al., 2003), social cognitive theory
6	Kandoth & Shekhar (2022)	Theory of reasoned action (TRA; Ajzen & Fishbein, 1977), technology acceptance model (TAM; Davis, 1989), unified theory of acceptance and use of technology (UTAUT; Venkatesh et al., 2003)
7	Köchling & Wehner (2023)	Organizational justice theory, media richness theory, Gilliland's model (1993)
8	Köchling et al. (2023)	Theory of planned behavior (TPB), Gilliland's model (1993), affective response model
9	Langer et al. (2020)	Faking model (Levashina & Campion, 2006), process model of self-presentation (Marcus, 2009), media richness theory (Daft & Lengel, 1986), Gilliland's model (1993)
10	Langer et al. (2021)	Application reaction theories (e.g., Gilliland, 1993)
11	Leutner et al. (2023)	(explanation of concepts but no explicit mentioning of theories)
12	Mirowska & Mesnet (2022)	Models of (organizational) justice (e.g., Gilliland, 1993), signaling theory

No.	Study	Theories used
13	Noble et al. (2021)	Organizational justice theory (e.g., Gilliland, 1993)
14	Schick & Fischer (2021)	Gilliland’s model (1993), integrated model of fit from the organization and applicant perspectives (Ostroff & Zhan, 2012)
15	Suen et al. (2019)	Social information processing theory, lens model (Brunswik, 1956), media richness theory (Daft & Lengel, 1986), social interface theory (Long, 2001), Gilliland’s model (1993)
16	Van Esch & Black (2019)	(explanation of concepts but no explicit mentioning of theories)
17	Van Esch et al. (2019)	(explanation of concepts but no explicit mentioning of theories)
18	Wang et al. (2021)	Flow theory, innovation diffusion theory (IDT), theory of planned behavior (TPB), theory of reasoned action (TRA), technology acceptance model (TAM)
19	Wesche & Sonderegger (2021)	Gilliland’s model (1993)

Table C3

Practical Considerations

No.	Study	Practical consideration
1	Acikgoz et al. (2020)	• Embedding a certain amount of human interaction within AI-based staffing systems (even at early stages)
2	Bedemariam & Wessel (2023)	• Humanizing the AI and/or educating the applicant pool on how the AI is used • Mix of human and AI decision-making • Development of AI selection systems that can lessen fairness perception gap between racial groups
3	Chen (2023)	• Companies with ideas for large-scale implementations of AI recruitment systems should be cautious, as organizational changes suffer setbacks (Black & Gregersen 2013*) • Companies should provide transparency about the algorithm development process, and the training of program developers to prevent unconscious bias (Miller et al. 2018*)
4	Duong & Pham Thi (2022)	• Companies should give job seekers an appropriate degree of mastery, such as flexibility in recruitment time points • Enterprises can share information and popularise knowledge for job seekers before AI recruitment
5	Horodyski (2023)	• Advantages of the use of AI in recruitment: saves time, easy to use, improves the quality and objectivity of the recruitment process, better candidates experience, and enhances the employer's brand

No.	Study	Practical consideration
5	Horodyski (2023)	• Disadvantages of the use of AI in recruitment: AI tools lack the nuances of human judgment, issues with low accuracy and reliability, immature technology, lack of transparency, ethical, legal, and privacy issues
6	Kandoth & Shekhar (2022)	• (not mentioned in the article)
7	Köchling & Wehner (2023)	• Careful evaluation of the potential adverse effects of AI support on organizational attractiveness to prevent losing talented applicants • If the technology is well-designed, organizations should consider ways to improve their applicants' perceptions and try to reconcile the advantages with the individual applicant's needs (e.g., giving applicants a suitable explanation of why an AI-supported selection tool is used) • Organizations should try to create a personal environment • Recruiters should keep in mind that AI-supported selection tools can lead to unfair treatment if the underlying training data set is unbalanced or contains discrimination, or if the system is poorly designed
8	Köchling et al. (2023)	• Companies should avoid using AI-based video and telephone interviews in the application process without explaining and communicating the new situation to their applicants (Langer et al. 2020*; van Esch et al. 2019*) • Companies can use algorithmic decision-making-based CV screening without concern about the negative reactions of applicants • Companies could explain how the new technologies work and how they support human decisions

No.	Study	Practical consideration
8	Köchling et al. (2023)	• Companies could rely on a combination of AI-based selection tools and human-assisted process steps • Companies using AI-based selection tools should monitor if the usage yields to the candidate's withdrawal from the selection process • Companies should not try to hide their usage of AI-based selection methods
9	Langer et al. (2020)	• Applicants' use of deceptive impression management might be reduced by using automatic evaluation of interviews
10	Langer et al. (2021)	• If organizations provide applicants with information about automated selection situations, they should include justification about why this selection procedure is used (e.g., emphasizing benefits for applicants, job-relatedness, and validity in screening the best applicants are viable pieces of information that can be provided to applicants) • Limiting information when using systems in certain domains • By trying to diminish negative reactions through information, organizations could actually worsen them • Organizations might be advised to cut down on available information about AI-based automated systems
11	Leutner et al. (2023)	• (not mentioned in the article)
12	Mirowska & Mesnet (2022)	• The balance between artificial intelligence evaluation and human contact should be carefully considered, avoiding selection systems that are predominantly centered on artificial intelligence evaluation

No.	Study	Practical consideration
12	Mirowska & Mesnet (2022)	• Organizations should pay close attention to the level of humanizing of the AI • Organizations should strive to fulfill expectations of informational justice, by transparently revealing their use of artificial intelligence evaluation and explaining their reasons for this choice • Organizations should make the decision to implement artificial intelligence evaluation strategically, recognizing not only the potential to 'label' those individuals with certain characteristics who may be drawn to its use (Acikgoz, 2019*), but also the potential for the exclusion of candidates on criteria that may not be clearly linked to job performance
13	Noble et al. (2021)	• Organizations should use algorithms properly • Justice perceptions could be inspired by a description that lets applicants know the algorithm has been vetted extensively prior to deployment and shown to produce valid, fair, and high-quality screening decisions • Trust in the job-relatedness of an algorithmic screening procedure could be built through transparency • Employers may wish to create and publicize communication channels that can be used by applicants who have questions or would like to be reconsidered
14	Schick & Fischer (2021)	• HR managers should provide cues of high system reliability
15	Suen et al. (2019)	• Asynchronous-based interviewing can be used to decrease the impressionable primacy effect and bias, which significantly influences selection decisions by interviewers (Florea et al., 2019*)

No.	Study	Practical consideration
15	Suen et al. (2019)	• Automatic asynchronous video interviews plus AI decision agent may avoid the procedural justice issue, and this interview modality should be considered as a potential alternative to synchronous-based interviews conducted by human interviewers, which entail higher costs and greater restriction regarding scheduling (Torres & Gregory, 2018*) • Employers or recruiters should be aware of the disadvantages of using asynchronous interview platforms due to the lower level of human interaction, which may cause withdrawal behaviors in applicants
16	Van Esch & Black (2019)	• Importance of the selection of the exact provider or tool • Firms have to take care to integrate what they do with AI recruiting so as to ensure that from a candidate's point of view the total recruiting experience is not less than the sum of the parts
17	Van Esch et al. (2019)	• HR practitioners need to ensure a multipronged approach to influence the target market of desired job applicants (Maurer & Liu, 2007*) • HR practitioners must be aware that the uptake or not of AI-recruitment processes has the potential to cause separated actors
18	Wang et al. (2021)	• HR managers can focus more on integrating AI tools with their e-recruitment services to provide better services to the end-user for better outcomes • HR managers can use AI tools in both cases to assess the job applicant's physiological and psychological aspects (online and offline assessment) • An HR person can develop e-strategic goals with AI recruitment to implement the organization's vision

No.	Study	Practical consideration
18	Wang et al. (2021)	• HR practitioners need to ensure a multipronged approach to influence desired job applicants (Black & van Esch, 2020*; Puncheva-Michelotti, Hudson, & Jin, 2018*)
19	Wesche & Sonderegger (2021)	• Organizations should carefully evaluate whether, and if so, in which stages of the selection process they implement automation and how they communicate it in job advertisements • Possible way to alleviate potential negative effects of communicating the use of automated selection procedures could be to counteract the information with additional information that may positively target job-seekers' beliefs regarding AI-based selection tools

Note. * Indicates studies referred to by the authors of the included articles.