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ARTICLE

Applicant reactions to algorithm- versus recruiter-based evaluations of an asynchronous video interview and a personality inventory

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Abstract

In two studies, we examined the effects of algorithm-based (vs. recruiter-based) evaluations of an asynchronous video interview and a personality inventory on applicant reactions. In line with our expectations, we found several negative applicant reactions to the use of algorithms. Specifically, in Study 1 ($N=172$), informing participants that an algorithm, rather than a recruiter, had analysed their interview and personality inventory increased feelings of emotional creepiness, and reduced fairness perceptions, perceived predictive validity and feedback acceptance. In Study 2 ($N=276$), we were able to replicate these effects for fairness perceptions and perceived predictive validity. Furthermore, in both studies, algorithm-based evaluations negatively affected feedback acceptance, organizational attraction and job acceptance intentions through fairness perceptions. However, in contrast with our expectations, selection decision favourability did not influence the impact of evaluation source (recruiter vs. algorithm) on applicant reactions. In Study 2, we also found some tentative evidence that applicant reactions to algorithm-based evaluations are not affected by the type of information source (i.e. verbal vs. nonverbal cues) on which the algorithm is based.

KEYWORDS

algorithms, applicant reactions, asynchronous video interviews

Practitioner Points

- The benefits of algorithm-based evaluations include efficiency in terms of time and costs and increased standardization of the process.
- To fully reap these benefits, organizations should also consider applicant reactions; unfavourable reactions can damage organizations' image and reputation.
- The present study indicates that applicants show unfavourable reactions to the use of algorithm-based evaluations.
- These negative reactions are independent of the selection decision or the specific cues on which algorithms are based.

INTRODUCTION

The COVID-19 crisis has accelerated the use of innovative techniques in selection contexts, including algorithm-based evaluations (Maurer, 2020; Woods et al., 2020). Algorithm-based evaluations rely on technology that automates decision-making and replaces or augments the recruiter in the assessment of applicants' attributes (Mirowska, 2020). Specifically, the use of algorithms to evaluate asynchronous video interviews (AVIs)—one-way digital interviews in which applicants do not interact with an organizational representative (Lukacik et al., 2022)– has attracted a lot of interest (Chamorro-Premuzic et al., 2017; Mirowska & Mesnet, 2022). The benefits of this technique include efficiency in terms of time and costs and increased standardization of the process (Suen et al., 2019). However, to fully reap these benefits, organizations might also like to consider applicant reactions; unfavourable reactions can damage their image and reputation as a good employer (Steiner, 2017) and negatively impact employees' work attitudes (McCarthy et al., 2017).

There are several reasons why applicants might react negatively to being evaluated by an algorithm. For instance, applicants are generally unfamiliar with algorithms, which makes them appear less legitimate (Mirowska & Mesnet, 2022). Furthermore, algorithms often evaluate information that is not within applicants' control. For example, applicants cannot easily change or modify the timbre of their voice, their mannerisms or their facial expressions. Hence, the use of these information sources can raise ethical concerns (Tippins et al., 2021). Indeed, several studies have shown that algorithm-based evaluations (vs. recruiter-based evaluations) generally have a negative impact on applicant reactions (Acikgoz et al., 2020; Langer et al., 2020, 2021; Mirowska, 2020; Suen et al., 2019; Wesche & Sonderegger, 2021).

Although these studies have been insightful, they suffer from three limitations that affect their external validity. First, the majority of these studies relied on vignettes describing the selection procedure (Acikgoz et al., 2020; Langer et al., 2021; Mirowska, 2020; Wesche & Sonderegger, 2021). It remains unclear whether these results generalize to settings in which participants actually experience the hypothetically induced scenarios. Second, apart from the study by Acikgoz et al. (2020), participants in these studies reported their reactions without being aware of the selection decision. This is problematic because being invited to the next selection round or receiving a job offer is an important driver of applicant reactions (Tippins et al., 2021) and may moderate the effects of selection procedures on applicant reactions (McCarthy et al., 2017). Third, previous studies on applicant reactions treated algorithms as homogeneous tools and ignored that algorithms differ widely in the type of information they include: some algorithms are based on verbal, paraverbal and nonverbal cues, whereas other algorithms only include verbal cues (Kahn, 2021). As a result, it is currently unknown how such design choices affect applicant reactions.

Our goal is to advance research on applicant reactions by conducting two studies in which we examine the effects of algorithm-based (vs. recruiter-based) evaluations on applicant reactions after they have experienced the selection procedure and have been informed about the selection decision. Our design closely mirrors laws, guidelines and practices in countries (e.g. European countries, European Commission, 2022) or states (e.g. California or Georgia, Electronic Privacy Information Center, 2022) where no AI-specific laws are yet in place, and where organizations commonly explain how (automated) scores are calculated in the reporting phase of a selection procedure (Dutch Association of Psychologists, 2017). Furthermore, as most selection procedures include several tools (Ryan et al., 2015), we created a procedure consisting of two often-used pre-screening methods: an AVI and a personality inventory (Basch et al., 2022).

Besides providing a rigorous test of how applicants react to algorithm-based evaluations in a realistic selection procedure, the present study contributes to the literature in two other ways as well. First, we expand the theoretical lens of studies on applicant reactions to algorithm-based evaluations by introducing two theoretical frameworks to this field: social exchange theory (SET; Blau, 1964; McClintock et al., 1984) and the applicant attribution-reaction theory (AART; Ployhart & Harold, 2004). Research on applicant reactions to algorithm-based evaluations largely builds on Gilliland's (1993) justice model and signalling theory (Bangerter et al., 2012; Spence, 1973). However, as applicant reactions studies 'are moving beyond the justice model' (McCarthy et al., 2017, p. 1697), it is important to show how more recent theories in applicant reactions research can be used to explain reactions to algorithm-based evaluations as well as the role of selection decision favourability. Expanding our knowledge of reactions among rejected applicants is especially important (as selection procedures generally lead to more rejected than accepted applicants) and constitutes a first step towards designing effective interventions.

Second, to our knowledge, the present study is the first to examine how applicants react to decisions that are based on their nonverbal cues—behaviours over which they have little control (Tippins et al., 2021) and that are known to show biases (Singer & Metz, 2019). Thus, we advance research on new technology in personnel selection (Brenner et al., 2016; Lukacik et al., 2022) by examining how the use of different information sources (i.e. verbal vs. nonverbal cues) affects applicant reactions to algorithm-based evaluations. Organizations wishing to increase applicant reactions to algorithm-based evaluations may want to use these outcomes in their algorithm design.

Applicant reactions to algorithm-based evaluations

Existing theory

As there is no single, overarching theoretical framework of applicant reactions, studies on applicant reactions often draw on a combination of frameworks (Acikgoz et al., 2020; McCarthy et al., 2017; Wesche & Sonderegger, 2021). The two most often applied frameworks in studies on applicant reactions to algorithm-based evaluations are Gilliland's (1993) justice model and signalling theory (Bangerter et al., 2012; Spence, 1973).

Gilliland's (1993) model, rooted in organizational justice theory, is the most influential theoretical framework within the applicant reactions field (McCarthy et al., 2017; Ryan & Ployhart, 2000). According to Gilliland's model, situational (e.g. recruiters) and personal (e.g. performance expectations) conditions influence the extent to which procedural (e.g. job relatedness) or distributive (e.g. equity) rules are perceived as violated or satisfied. The combined perceptions of these justice violations and satisfactions form an applicant's overall evaluation of the fairness of the selection procedure, which in turn influences the applicant's attitudes and behaviours (see, Gilliland, 1993, for a more detailed description of the theory). Gilliland's model also indicates that procedural justice rules have an even greater impact on the applicant's attitudes and behaviours when distributive rules have been violated (e.g. when applicants are rejected).

In the context of an AVI, Acikgoz et al. (2020) tested the entirety of Gilliland's (1993) justice model, while Langer et al. (2021) focused on how process information and process justification affected fairness perceptions and subsequent organizational attractiveness. Furthermore, Wesche and

Sonderegger (2021) examined how information on the automation of application-document screening in a job advertisement affected expected fairness and procedural justice. Arguments for why algorithm-based evaluations violate justice rules include the lack of personal contact, and because interpersonal dynamics may be perceived as job relevant (Acikgoz et al., 2020). Furthermore, applicants do not have enough knowledge and understanding of how algorithms weigh certain information. Thus, when applicants are informed that they have been evaluated by an (unfamiliar) algorithm, they may feel that they have not been offered a fair chance to show their potential and therefore will react more negatively to this type of evaluation (Acikgoz et al., 2020; Langer et al., 2020; Noble et al., 2021).

Over the years, the theoretical lens of applicant reactions research has expanded (McCarthy et al., 2017), and studies have moved beyond Gilliland's (1993) justice model. One of these alternative theories is signalling theory (Bangerter et al., 2012; Spence, 1973). Signalling theory suggests that each social situation involves a signalling system consisting of a sender, a receiver and a signal that is associated with an unobservable characteristic of the sender (Connelly et al., 2011). In selection contexts, applicants have information that is not directly available to representatives of the organization (e.g. personality or skills), while these representatives have information that is not directly available to applicants (e.g. organizational culture; Bangerter et al., 2012). Both parties have to infer this information based on the signals that are sent during the selection procedure.

Signalling theory has been used in the majority of studies on applicant reactions to algorithm-based evaluations (Acikgoz et al., 2020; Mirowska, 2020; Mirowska & Mesnet, 2022; Wesche & Sonderegger, 2021). For example, in their interview study, Mirowska and Mesnet (2022) found that, for some applicants, the use of algorithm-based evaluations can signal that organizations are innovative, efficient and focus on objectivity. However, participants overwhelmingly felt that the use of algorithm-based evaluations signals that an organization does not value human contact. Similarly, Wesche and Sonderegger (2021) found that, by using automated procedures, organizations signal that they care about consistency and objectivity, but also signal a lack of human touch and appreciation towards applicants. Generally, perceptions of recruiters' warmth are a more important predictor of applicant reactions than perceptions of consistency (Wilhelmy et al., 2019). The use of algorithms may also restrict an applicant's pallet of signals. Indeed, participants believe they have a lower chance to perform when evaluated by an algorithm (Acikgoz et al., 2020), believe that a recruiter is easier to influence and expect that costly job-relevant cues (e.g. education) are more important when evaluated by an algorithm rather than a recruiter (Langer et al., 2023). Although signalling theory fits well within the context of applicant reactions to algorithm-based evaluations, it does not make any predictions about the role of decision favourability.

Expanded theoretical focus

There are two other theories that also offer plausible explanations for applicant reactions to algorithm-based evaluations, specifically after applicants have been informed about the selection decision: SET (Blau, 1964; McClintock et al., 1984) and the AART (Ployhart & Harold, 2004).

SET is concerned with the processes and principles that regulate the exchange of material or nonmaterial resources (Blau, 1964; McClintock et al., 1984). A basic tenet of SET is that, over time, relationships evolve into mutual commitments characterized by trust and loyalty. However, for this to happen, parties must abide by certain rules (Cropanzano & Mitchell, 2005). One of these rules is that valued resources are exchanged through a process of reciprocity, whereby a good deed of one party is repaid by a good deed from the other party (Gouldner, 1960). A breach of this rule tends to result in negative emotionally charged reactions (Piccoli & De Witte, 2015). SET forms the basis of various organizational phenomena, including the psychological contract (Dabos & Rousseau, 2004; Rousseau, 1990), which refers to 'the idiosyncratic set of reciprocal expectations held by employees concerning their obligations (what they will do for the employer) and their entitlements (what they expect to receive in return)' (McLean Parks et al., 1998, p. 698).

SET can also be used to explain applicant reactions to algorithm-based evaluations. Applying this framework to selection contexts, a social exchange relationship would begin with an applicant applying to an organization. By doing so, applicants invest time and effort into their application and make themselves vulnerable to the organization (e.g. by sharing sensitive data). Accordingly, they expect the organization to invest time and effort in carefully evaluating their data. According to Anderson (2011), such expectations are part of the pre-employment psychological contract between an applicant and an organization. When using an algorithm, there is no organizational representative who spends time evaluating applicants' profiles or test scores, and it remains unclear how their data will be treated. Hence, using algorithm-based evaluations violates the rule of reciprocity (or the pre-employment contract) and therefore should result in negative applicant reactions. Moreover, being rejected and thus receiving nothing in return for the invested time and effort may further violate the rule of reciprocity (Anderson, 2011), and lead to even stronger negative reactions.

A final theory that may increase our understanding of applicant reactions to algorithm-based evaluations is the AART (Ployhart & Harold, 2004). The AART applies basic principles of attribution theory (Weiner, 1985) to selection contexts. In general, people have the tendency to attribute success to internal, stable and controllable factors, and failure to external, unstable and uncontrollable factors (Weiner, 1985). These so-called self-serving attributions serve as a buffer to protect oneself from lowered self-esteem (Abramson et al., 1978). According to the AART, applicant reactions to selection decisions are fundamentally driven by such attributional processes. Indeed, in line with the AART, previous research has indicated that applicants display a tendency to use self-serving attributions, causing them to show positive reactions when the selection decision is favourable and negative reactions when the decision is unfavourable (Ababneh et al., 2014; Oostrom et al., 2012; Schinkel et al., 2013).

For two reasons, we expect applicants' self-serving attributions to be even stronger when they are evaluated by an algorithm instead of a recruiter. First, attribution formation happens primarily when an event is surprising and novel (Wong & Weiner, 1981), which is likely to be the case when applicants hear that they have been evaluated by an algorithm. Second, people apply social rules, norms and expectations when they interact with computers and algorithms (Hong et al., 2020). Importantly, in some situations, people consider computers to be more intelligent than humans (Sundar & Kim, 2019; for exceptions, see Rieger et al., 2022), and even more intelligent when they provide criticism rather than praise (Nass et al., 1994). Hence, a negative evaluation by an algorithm should pose an even greater threat to one's self-esteem than a negative evaluation by a recruiter, which, in turn, should trigger stronger self-serving attributions.

Hypothesis development

As there is no overarching set of applicant reactions (McCarthy et al., 2017), it is common to study a variety of reactions simultaneously, often derived from different frameworks (Hausknecht et al., 2004; McCarthy et al., 2017; Ryan & Ployhart, 2000). In the present study, we draw on five often studied applicant reactions that fit within Gilliland's (1993) model. Based on earlier reviews of applicant reactions (Hausknecht et al., 2004; McCarthy et al., 2017; Ryan & Ployhart, 2000), we organized these five reactions into reactions towards the procedure (fairness perceptions, face validity, perceived predictive validity) and reactions towards the organization and job (i.e. organizational attraction and job acceptance intentions). However, as applicant reactions research has expanded its focus beyond Gilliland's (1993) model (McCarthy et al., 2017), we also included two applicant reactions that are particularly relevant when examining reactions to algorithm-based evaluations after applicants have been informed about the selection decision: emotional creepiness and feedback acceptance. Emotional creepiness is an affective reaction towards unpredictable situations or technologies (Langer & König, 2018) and falls into the category of applicant reactions towards the procedure. Feedback acceptance combines applicants' cognitive reactions towards the procedure and their sense making of the situation (i.e. the extent to which feedback fits how applicants think about themselves; Morgeson & Ryan, 2009). Following Hausknecht et al. (2004), we present these self-perceptions as a separate category. Hence, we divide the applicant reactions in three conceptually distinctive categories: reactions towards (1) the selection procedure (i.e. fairness perceptions, face validity, perceived predictive validity and emotional creepiness), (2) the feedback (i.e. feedback acceptance) and (3) the organization and the job (i.e. organizational attraction and job acceptance intentions). Below, we provide definitions of the different applicant reactions and discuss additional reasons—next to the theories described above—for why we expect the use of algorithm-based evaluations to have a negative impact on these specific applicant reactions.

Applicant reactions towards the selection procedure

Of all factors in Gilliland's (1993) justice model, fairness, face validity and perceived predictive validity are the most widely examined reactions and have received the strongest research support (Hausknecht et al., 2004; Ryan & Ployhart, 2000). Within this model, fairness perceptions are defined as reactions to the satisfaction or violation of justice rules, face validity as the extent to which an assessment appears to measure content relevant to the job's characteristics, and perceived predictive validity as the extent to which as assessment appears to predict performance. A specific type of applicant reaction that can be caused by interacting with innovative technologies is emotional creepiness, which is defined as the unpleasant feeling elicited by unpredictable situations, and is often paired with uncertainty about how to behave (Langer & König, 2018).

Applicants will generally be unfamiliar with algorithm-based evaluations, and such evaluations are often based on nontransparent parameters (Pasquale, 2015). This makes it difficult for applicants to understand to what extent these evaluations are relevant for the job. Furthermore, algorithms often assess applicants' nonverbal information (e.g. facial expressions), which lacks predictive evidence (Tippins et al., 2021) and, because this information is not within applicants' control, may increase feelings of uncertainty. Notably, when applicants are evaluated by an algorithm, they do not interact with any representative of the organization, which may also create an alienating experience (Langer et al., 2017). Additionally, unless applicants apply for a job in the computer industry (e.g. software engineer), their future job is more likely to involve human-based than algorithm-based interactions. Hence, there is a mismatch between how applicants are being treated during the selection procedure and how they expect to be treated on the job.

> **Hypothesis 1a.** Applicants react more negatively towards the selection procedure (in terms of fairness, face validity, perceived predictive validity and emotional creepiness) when they are informed that they have been evaluated by an algorithm rather than a recruiter.

Applicant reactions towards the feedback

Feedback acceptance refers to applicants' beliefs that this feedback represents an accurate representation of their performance (Ilgen et al., 1979). Next to the valence of the feedback, assessor credibility is a key antecedent of feedback acceptance (Ilgen et al., 1979), also among assessment candidates (Boudrias et al., 2014). Besides the reasons described above, applicants might also perceive feedback from an algorithm as less credible than feedback from a recruiter because they may have the impression that recruiters are more likely to notice their unique qualities and circumstances, where an algorithm operates in a standardized manner. As people have a need to see themselves as unique and distinct from others (i.e. uniqueness theory, Snyder & Fromkin, 1980; optimal distinctiveness theory, Brewer, 1991), they could be less likely to accept algorithm-based evaluations than recruiter-based evaluations, regardless of whether this feedback is positive or negative.

> **Hypothesis 1b.** Applicants are less likely to accept feedback that is derived from algorithm-based evaluations as compared to recruiter-based evaluations.

Applicant reactions towards the organization and the job

The vast majority of applicant reactions research has emphasized the importance of studying organizational attraction and job acceptance intentions because of their strong link to job acceptance decisions (Carless, 2005; Hausknecht et al., 2004). Organizational attraction is defined as a positive attitude or affect towards an organization that leads to a desire to initiate a relationship with that organization (Aiman-Smith et al., 2001), and job acceptance intentions as the likelihood that an applicant would accept a job offer if one were forthcoming (Chapman et al., 2005). Applicants place a lot of weight on what they imagine the organization is like when forming perceptions of organizational attraction and acceptance intentions (Cable & Judge, 1996). Thus, providing impersonal signals by using algorithm-based evaluations is an important reason why algorithm-based evaluations could reduce organizational attraction and acceptance intentions for most applicants.

> **Hypothesis 1c.** Applicants react more negatively towards the organization and the job (in terms of organizational attraction and job acceptance intentions) when they are informed that they have been evaluated by an algorithm rather than a recruiter.

Selection decision favourability

Based on Gilliland's (1993) justice model, SET (Blau, 1964; McClintock et al., 1984), and the AART (Ployhart & Harold, 2004), we expect the reactions to algorithm-based evaluations to be even more negative when the selection decision is unfavourable. According to Gilliland (1993), procedural justice rules have an even greater impact on applicant reactions when distributive rules have been violated. Similarly, SET predicts that being rejected by an algorithm would result in even stronger violations of the rule of reciprocity than being rejected by a recruiter. Finally, in line with the AART, self-serving attributions should be stronger when applicants are evaluated by an algorithm instead of a recruiter, because of the novelty of algorithm-based evaluations (Wong & Weiner, 1981) and the intelligence ascribed to computers (Sundar & Kim, 2019).

> **Hypothesis 2.** Selection decision favourability (positive vs. negative) interacts with the source of the evaluation (algorithm vs. recruiter) in predicting applicant reactions, such that applicants show an even stronger negative reaction towards algorithm-based evaluations (compared to recruiter-based evaluations) when the decision is negative.

The role of information source

In their review of applicant reactions research, McCarthy et al. (2017) considered the circumstances under which applicants perceive technological means in personnel selection differently a key topic for future research. Since, applicant reaction research still treats algorithms as monolithic, whereas in reality algorithms can include a wide variety of information sources, especially when evaluating the recordings from AVIs. For example, organizations can choose to only focus on applicants' words (e.g. their interview transcripts) or use all data captured in the recorded videos, including nonverbal and paraverbal cues.

There are two reasons to believe that the use of different information sources may lead to different reactions. First, information sources can be distinguished along a continuum (Oswald, 2020), with intentional or controllable responses on one end of the continuum (e.g. answers to interview questions) and incidental data that are less intentional or controllable on the other end of the continuum (e.g. facial expressions or vocal patterns; see also DePaulo, 1992). In general, the feeling of—or actual—controllability is an important predictor of applicant reactions (Blacksmith et al., 2016; Langer et al., 2017). Second, facial expressions or vocal patterns may also disadvantage applicants who look, move or speak differently because of their origins, gender, age or physical abilities. Indeed, vocal patterns and facial expressions differ across race (Jack et al., 2009; Xue & Hao, 2006), gender (Houstis & Kiliaridis, 2009; Whiteside, 1996) and age (Houstis & Kiliaridis, 2009; Ohno & Hirano, 2014), and are affected by certain (motoric) physical disabilities (Movérare et al., 2017). Furthermore, facial recognition software is known to show racial biases (Cavazos et al., 2020):

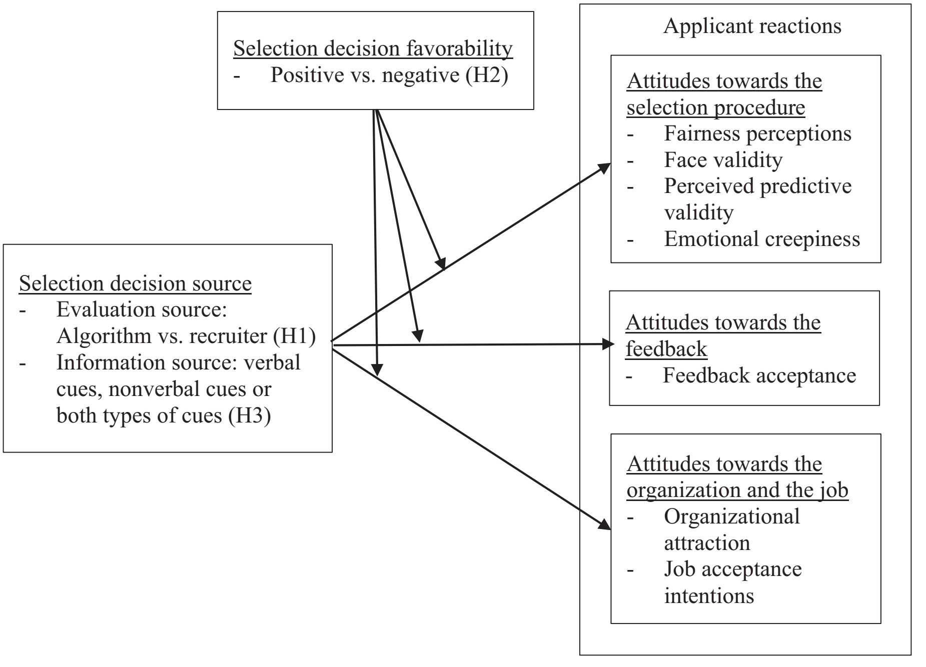

FIGURE 1 Research model.

algorithms falsely identify African-American and Asian faces 10 to 100 times more than Caucasian faces (Singer & Metz, 2019). Importantly, there is no evidence linking facial expressions and vocal patterns to job performance (Tippins et al., 2021). Hence, using these job-irrelevant cues may raise ethical concerns among applicants. Indeed, knowledge about these issues has also found its way to the general public through widely viewed documentaries (Kantayya, 2020). This leads to the following hypothesis:

> **Hypothesis 3.** Applicants react more negatively towards an algorithm that is based on a combination of verbal and nonverbal information or solely on nonverbal information as compared to an algorithm that is solely based on verbal information.

Figure 1 depicts our research model. We test our hypotheses in two studies, in which selection decisions are ostensibly based on an AVI and a personality inventory. For both studies, we obtained ethical approval and preregistered the hypotheses and methods on the Open Science Framework (https://osf.io/54vzx/?view_only=c861e6c85bc245fd8c9c6fcbb3f1b33a).

STUDY 1

The goal of Study 1 was to test Hypotheses 1 and 2.

Materials and methods

Procedure

We recruited a sample of working adults (19–66 years old) via Prolific, a crowdworking platform dedicated to academic research (Peer et al., 2017). We targeted native English-speaking participants living in the United States. We used a 2 (algorithm vs. recruiter) × 2 (positive vs. negative decision) between-subjects design, for which a power analysis (Faul et al., 2009) showed that the minimum required sample size was 128 to have 80% power to detect a medium-sized moderation effect of selection decision favourability (based on Horvath et al., 2000; Rolland & Steiner, 2007). As we expected quite some failed attention and manipulation checks, we oversampled participants to account for possible exclusions. Hence, we ceased recruitment after more than 400 participants completed the first part of the study. We paid our participants \$9 (\$8 for Part 1 and \$1 for Part 2).

The study consisted of two parts. In the first part, we obtained informed consent and presented our participants with a fictitious job advertisement for a management traineeship. We asked them to imagine that they are an applicant and that they are about to apply for the job presented in this advertisement. We also explained that the selection procedure would consist of an online interview and a personality inventory, and that a week later they will receive feedback on their personality and suitability for the management traineeship based on their scores on these two tools. Next, we presented participants, via text display, eight past-behavioural interview questions, four pertaining to Extraversion and four to Conscientiousness, both valid predictors of leadership effectiveness (Judge et al., 2002). Participants replied to these questions by talking to their screen, which showed the recorded webcam image of themselves. Subsequently, we asked them to complete the HEXACO-60 (Ashton & Lee, 2009) and to provide some basic demographic information. Upon completion of the AVI and the HEXACO-60, we asked participants to rate organizational attraction and job acceptance intentions (baseline measures), their interest in the management traineeship, and their self-assessed performance on the AVI.

A week later, we invited our participants to the second part of the study. Before the invitation was sent, we calculated the means and *SD*s for the HEXACO-60 Extraversion and Conscientiousness scale based on a large norm group (N = 2414; part of the data is reported in De Vries et al., 2009). We classified participants who scored 1/3 *SD* above average on the two scales to be accepted, while participants scoring below this cut-off value were classified to be rejected. This cut-off value split the participant pool equally across decision favourability conditions. Upon opening the survey, participants were randomly assigned to one of the evaluation source conditions.

The survey started with the decision letter (Table 1), in which we explained whether the participant was rated by a recruiter or an algorithm, reported the participants' normed quintile scores on Extraversion and Conscientiousness (e.g. 'Above average'), and indicated whether or not they were invited to the next round. Participants were also presented with a short explanation of Extraversion and Conscientiousness. After reading the decision letter, we asked participants to briefly describe their initial reaction to ensure they reflected on the content of the decision letter. Note that we made the participants believe their scores were based on the AVI and the HEXACO-60. However, because there is considerable evidence for the validity of the HEXACO inventory (Ashton et al., 2014), while validity evidence for AVIs is still accumulating (Woods et al., 2020), we based the selection decision solely on participants' scores on the HEXACO-60. This also allowed us to have Part 2 of our research take place a week after Part 1, as scoring participants' answers to the AVI questions would have taken us considerably longer than that. After reading the decision letter, we measured participants' reactions.[1]

As a manipulation check, participants were asked to indicate the outcome of the selection decision (answer options: 'Positive—I was invited for the next selection round', 'Negative—I was rejected', 'I don't know') and how their interview and personality inventory were assessed (answer options: 'By a recruiter', 'Via an algorithm', 'I do not know'). Participants who failed one or both manipulation checks (i.e. if they provided the wrong answer or indicated 'I do not know') were removed from the data set. In addition, we included an attention check item ('Please select strongly agree on this item') in the

[1]Although some of the HEXACO scores were correlated with some of the applicant reactions, controlling for the HEXACO scores did not change our conclusions. Only the result for evaluation source on perceived predictive validity changes slightly: In Study 1, the F-value changes from 3.90 (p = .0499) to 3.30 (p = .071) and in Study 2, this the F-value changes from 3.78 (p = .053) to 3.97 (p = .047).

TABLE 1 Manipulations Study 1.

	Recruiter condition	Algorithm condition
Introduction in both the positive and negative selection decision favourability condition	Thank you for your interest in the Management Traineeship at '[fictitious name of the company]'. We make use of modern technology in our assessments. **However, we did not use** technology in the scoring phase**, but asked a recruiter to personally evaluate** candidates' profiles. Hence, **a** human assessor has looked at your profile at this stage of the selection procedure	Thank you for your interest in the Management Traineeship at '[fictitious name of the company]'. We make use of modern technology in our assessments. **Therefore, we also used** technology in the scoring phase **and used an algorithm to automatically screen** candidates' profiles. Hence, **no** human assessor has looked at your profile at this stage of the selection procedure
Explanation of personality ratings in both the positive and negative selection decision favourability condition	Based on the job interview and the personality questionnaire, **our recruiter** rated you on the following two characteristics: extraversion and conscientiousness. These characteristics have been demonstrated to be accurate indicators of success in management traineeships. Below you can find a description of these two characteristics	Based on the job interview and the personality questionnaire, **our algorithm** rated you on the following two characteristics: extraversion and conscientiousness. These characteristics have been demonstrated to be accurate indicators of success in management traineeships. Below you can find a description of these two characteristics
Results in both the positive and negative selection decision favourability condition	Your ratings are as follows: • Extraversion: '[very low, low, average, high, very high]' • Conscientiousness: '[very low, low, average, high, very high]'	Your ratings are as follows: • Extraversion: '[very low, low, average, high, very high]' • Conscientiousness: '[very low, low, average, high, very high]'
Decision in the positive selection decision favourability condition	Based on the ratings of the **recruiter**, we see an adequate match between your characteristics and the nature of the position. Therefore, we are glad to inform you that you have passed the first round and that we would like to invite you for a second, real-life job interview	Based on the ratings of the **algorithm**, we see an adequate match between your characteristics and the nature of the position. Therefore, we are glad to inform you that you have passed the first round and that we would like to invite you for a second, real-life job interview
Decision in the negative selection decision favourability condition	Based on the ratings of the **recruiter**, we did not see an adequate match between your characteristics and the nature of the position. Therefore, we decided not to pursue your candidacy at this time. We wish you the best of luck in your future job search and professional activities	Based on the ratings of the **algorithm**, we did not see an adequate match between your characteristics and the nature of the position. Therefore, we decided not to pursue your candidacy at this time. We wish you the best of luck in your future job search and professional activities

Note: The words that differed between the recruiter and the algorithm condition are indicated in bold.

HEXACO-60. Participants who failed this attention check, as well as participants who showed either very low ($SD < .70$) or very high ($SD > 1.60$) variability in their HEXACO-60 responses (e.g. noncompliant responders; Barends & De Vries, 2019; Lee & Ashton, 2018) were also removed from the data set.

Participants

A total of 409 participants completed the AVI and the HEXACO-60, of which 297 also completed the second part of our study. We removed 18 cases because they were incomplete, 46 cases because of a failed manipulation check regarding the outcome, 59 cases because of a failed manipulation check regarding the source of the selection decision, one case because of a failed attention check, and one case because of high variability in HEXACO-60 responses. Hence, our final sample consisted of 172 participants (47.1% men; 50% women; 2.9% other): 41 were rejected by the recruiter, 39 were accepted by the recruiter, 46 were rejected by the algorithm and 46 were accepted by the algorithm. Participants' mean age was 33.62 years ($SD = 11.91$). On average, participants had 13.01 years of work experience ($SD = 11.10$) and they had applied for 7.80 ($SD = 20.15$) jobs in the last 2 years. Our final sample did not differ in terms of age, gender, educational level, baseline measures of organizational attraction and job acceptance intentions, interest in the management traineeship and self-assessed performance on the AVI from the participants who only completed the first part of our study.

Measures

All items of the below scales were measured on a 7-point scale (1 = *strongly disagree* and 7 = *strongly agree*).

Fairness perceptions

Participants completed four items adopted from earlier research on fairness perceptions (Smither et al., 1993; Wiechmann & Ryan, 2003), with the only alteration that we replaced the more generic term 'job' with 'traineeship'.

Face validity and perceived predictive validity

Participants completed 10 items adopted from earlier research on job relatedness (Smither et al., 1993; Wiechmann & Ryan, 2003); five items measured face validity and five items measured perceived predictive validity. Again, we replaced the word 'job' with 'traineeship'. As the items came from a single scale, we conducted a confirmatory factor analysis to confirm the two-dimensional structure of the scale. A two-factor model provided a better fit to the data, $\chi^2(34) = 114.34$, $p < .01$, TLI = .89, CFI = .92, RMSEA = .12, SRMR = .06, than a one-factor model, $\Delta\chi^2(1) = 143.49$, $p < .01$, $\chi^2(35) = 257.83$, $p < .01$, TLI = .71, CFI = .77, RMSEA = .19, SRMR = .09.

Emotional creepiness

Emotional creepiness was measured with four items adapted from Langer and König (2018): we kept one item similar ('The selection procedure somehow feels threatening'), slightly altered two items to focus on situational characteristics rather than dispositions ('This selection procedure made me feel uneasy' instead of the original item, 'I feel uneasy about this selection procedure'; 'Somehow, this selection procedure made me feel afraid' instead of the original item, 'I have an undefinable fear about this selection procedure'), and we added a reverse-coded item ('This selection procedure made me feel comfortable').

Feedback acceptance

To measure participants' acceptance of the feedback, we used the 4-item scale developed by Tonidandel et al. (2002).

Organizational attraction
To measure organizational attractiveness, we used three items adopted from earlier research (Bauer & Aiman-Smith, 1996; Highhouse et al., 2003; Turban & Keon, 1993).

Job acceptance intentions
Job acceptance intentions were measured with two items adopted from Speer et al. (2016), with the only alteration that we replaced the word ‘job’ with ‘traineeship’. These items were selected because they can also, in case of a rejection letter, refer to a future application for a traineeship.

Confirmatory factor analyses
The results of a series of confirmatory factor analyses showed that a model in which the seven factors were allowed to covary ($\chi^2[303] = 619.35$, $p < .01$, TLI = .90, CFI = .91, RMSEA = .08, SRMR = .10), fit the data significantly better than a one-factor model ($\Delta\chi^2[21] = 1423.22$, $p < .01$, $\chi^2[324] = 2042.57$, $p < .01$, TLI = .49, CFI = .53, RMSEA = .18, SRMR = .13), or a three-factor model with the items measuring reactions towards the selection procedure, the feedback and the organization and the job loading on separate factors ($\Delta\chi^2[18] = 639.24$, $p < .01$, $\chi^2[321] = 1258.59$, $p < .01$, TLI = .72, CFI = .74, RMSEA = .13, SRMR = .10).

Control variables
We controlled for interest in the position and self-assessed performance on the AVI. We measured self-assessed performance with three items adopted from Wiechmann and Ryan (2003). Controlling for self-assessed performance is important as, in line with self-verification theory (Swann Jr., 2011), individuals tend to react more positively to feedback (in our case the selection decision) when this feedback is in line with their self-views (Ayduk et al., 2013). Furthermore, we asked participants to indicate the extent to which they were interested in the job. We controlled for interest in the position, as variation in participants' interest in the management traineeship could influence subsequent affective reactions (McCarthy et al., 2017).

Results

Table 2 presents the descriptive statistics, alpha coefficients and correlations of all study variables. Even though our potential control variables showed the expected pattern of correlations, controlling for these variables did not change our findings. Hence, we report the results of the analyses without control variables.

Hypothesis testing

To test our hypotheses, we conducted three series of (M)AN(C)OVAs (Table 3).

Applicant reactions towards the selection procedure
We found significant main effects for evaluation source (Wilk's $\lambda = .90$, $F[4, 165] = 4.76$, $p < .01$) and selection decision favourability (Wilk's $\lambda = .88$, $F[4, 165] = 5.76$, $p < .01$) in the expected directions, but no significant interaction effect (Wilk's $\lambda = .97$, $F[4, 165] = 1.35$, $p = .25$). Follow-up analyses revealed lower fairness perceptions ($F[1, 168] = 16.74$, $p < .01$, partial $\eta^2 = .09$), lower perceived predictive validity ($F[1, 168] = 3.90$, $p = .0499$, partial $\eta^2 = .02$) and higher emotional creepiness ($F[1, 168] = 5.26$, $p = .02$, partial $\eta^2 = .03$) when participants were evaluated by an algorithm rather than a recruiter. Thus, regarding reactions towards the selection procedure, Hypothesis 1a was largely supported and Hypothesis 2 was rejected.

TABLE 2 Means, standard deviations and correlations between study variables (Study 1).

	M	*SD*	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Demographics																	
1. Age	33.62	11.91	–														
2. Gender	.51	.50	.03	–													
Pre-decision reactions T0																	
3. Self-assessed performance	3.78	1.37	.10	−.20**	(.84)												
4. Interest in the job	4.90	1.66	.07	.06	.11	–											
5. Organizational attraction	5.02	1.29	.11	.11	.07	.64**	(.94)										
6. Job acceptance intentions	5.11	1.42	.13	.11	.10	.61**	.74**	(.83)									
Manipulations																	
7. Evaluation source	.54	.50	−.01	−.01	−.08	.07	.02	.09	–								
8. Selection decision favourability	.49	.50	.21**	.03	.23**	.22**	.14	.14	.01	–							
Post-decision reactions T1																	
9. Fairness perceptions	4.46	1.50	.15	−.03	.09	.17*	.20**	.07	−.29**	.27**	(.92)						
10. Face validity	4.78	1.28	.11	.07	.07	.17*	.21**	.16*	−.11	.12	.54**	(.88)					
11. Perceived predictive validity	3.75	1.31	.13	.01	.14	.19*	.21**	.13	−.14	.23**	.74**	.61**	(.85)				
12. Emotional creepiness	3.21	1.26	−.25**	.14	−.20**	−.04	−.06	.04	.16*	−.27**	−.47**	−.44**	−.36**	(.78)			
13. Feedback acceptance	4.84	1.36	.24**	−.03	.10	.20**	.20**	.12	−.18*	.35**	.58**	.48**	.55**	−.42**	(.83)		
14. Organizational attraction	4.34	1.57	.10	.00	.23**	.54**	.60**	.43**	−.06	.43**	.49**	.24**	.42**	−.33**	.37**	(.96)	
15. Job acceptance intentions	4.60	1.66	−.03	.08	.16*	.53**	.52**	.52**	.01	.28**	.35**	.22**	.28**	−.18*	.28**	.74**	(.89)

Note: $N = 172$. Gender is coded as 0 = man and 1 = woman. Evaluation source is coded as 0 = recruiter and 1 = algorithm. Selection decision favourability is coded as 0 = negative and 1 = positive. All other variables were measured on a 7-point scale. Alpha coefficients are presented on the diagonal. $^{**}p < .01$, $^{*}p < .05$ (two-tailed).

TABLE 3 Descriptive statistics and between-subjects tests (Study 1).

	Overall, *M* (*SD*)	Negative decision, *M* (*SD*)	Positive decision, *M* (*SD*)	*F* (partial η^2)		
				Evaluation source	Selection decision favourability	Interaction effect
Fairness perceptions				16.74** (.09)	15.13** (.08)	.04 (.00)
Recruiter	4.92 (1.38)	4.49 (1.48)	5.37 (1.13)			
Algorithm	4.06 (1.49)	3.67 (1.43)	4.45 (1.47)			
Face validity				2.09 (.01)	2.33 (.01)	2.72 (.02)
Recruiter	4.93 (1.19)	4.94 (1.15)	4.91 (1.25)			
Algorithm	4.65 (1.34)	4.34 (1.14)	4.95 (1.46)			
Perceived predictive validity				3.90* (.02)	10.00** (.06)	.07 (.00)
Recruiter	3.96 (1.24)	3.63 (1.19)	4.30 (1.21)			
Algorithm	3.58 (1.36)	3.30 (1.24)	3.86 (1.43)			
Emotional creepiness				5.26* (.03)	13.88** (.08)	.39 (.00)
Recruiter	2.99 (1.20)	3.27 (1.20)	2.70 (1.16)			
Algorithm	3.40 (1.28)	3.80 (1.23)	3.00 (1.21)			
Feedback acceptance				6.69* (.04)	23.68** (.12)	2.75 (.02)
Recruiter	5.07 (1.12)	4.80 (1.15)	5.41 (1.20)			
Algorithm	4.61 (1.45)	3.99 (1.47)	5.23 (1.12)			
Organizational attraction				.84 (.00)	39.41** (.19)	.44 (.00)
Recruiter	4.43 (1.61)	3.70 (1.47)	5.21 (1.39)			
Algorithm	4.25 (1.53)	3.64 (1.48)	4.86 (1.33)			
Job acceptance intentions				.00 (.00)	14.14** (.08)	.15 (.00)
Recruiter	4.59 (1.66)	4.18 (1.59)	5.01 (1.64)			
Algorithm	4.61 (1.68)	4.10 (1.79)	5.12 (1.40)			

Note: $N = 172$, with n per cell varying between 39 and 46. All variables were measured on a 7-point scale. Evaluation source is coded as 0 = recruiter and 1 = algorithm. Selection decision favourability refers to the valence of the selection decision and is coded as 0 = negative and 1 = positive. **$p < .01$. *$p < .05$.

Applicant reactions towards the feedback

We found significant main effects for evaluation source ($F[1, 168] = 6.69$, $p = .01$, partial $\eta^2 = .04$) and selection decision favourability ($F[1, 168] = 23.68$, $p < .01$, partial $\eta^2 = .12$) in the expected directions, but no significant interaction effect ($F[1, 168] = 2.75$, $p = .10$, partial $\eta^2 = .02$). Thus, Hypothesis 1b was supported, and Hypothesis 2 was rejected for feedback acceptance.

Applicant reactions towards the organization and the job

We found a nonsignificant main effect for evaluation source (Wilk's $\lambda = .99$, $F[2, 167] = .94$, $p = .39$), a significant main effect for selection decision favourability in the expected direction (Wilk's $\lambda = .81$, $F[2, 167] = 20.23$, $p < .01$) and a nonsignificant interaction effect (Wilk's $\lambda = .99$, $F[2, 167] = 1.01$, $p = .37$). Thus, Hypothesis 1c and Hypotheses 2 were rejected for reactions towards the organization and the job.

Exploratory analyses

Some applicant reaction models suggest that reactions towards the procedure affect more distal reactions (Gilliland, 1993; McCarthy et al., 2017). For example, McCarthy et al. (2017) argue that negative reactions

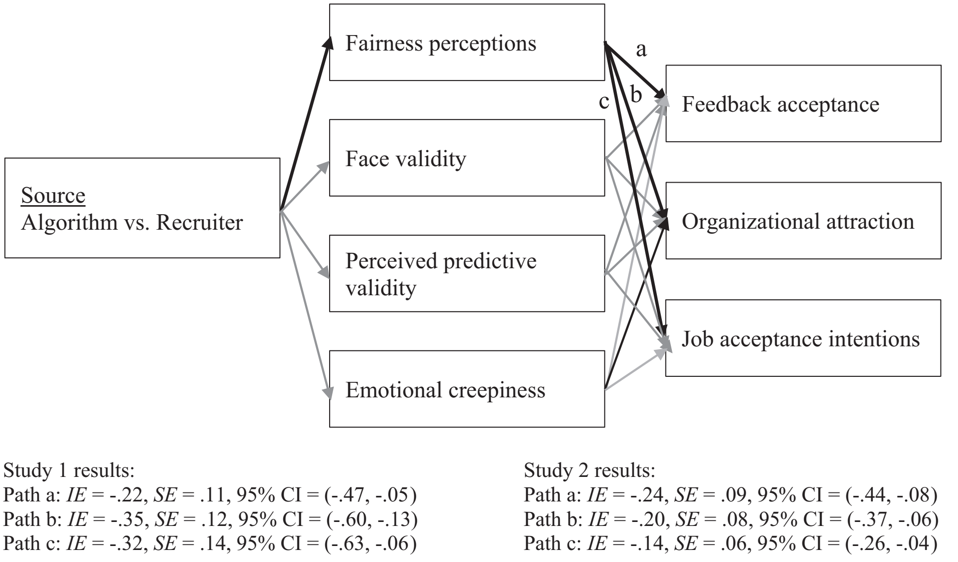

FIGURE 2 Results of the exploratory mediation analyses. *Note*: Results of the exploratory mediation analyses examining the indirect effects (IE) of evaluation source on the reactions towards the decision, the organization and the job through the reactions towards the procedure. The significant mediation paths are indicated in black and bold.

towards the procedure trigger negative affect and therefore result in adverse attitudes towards the feedback, organization and job. However, as the evidence for these mediating mechanisms is mixed (Acikgoz et al., 2020; Langer et al., 2017, 2021), we did not formulate specific hypotheses about these effects. Nonetheless, we explored whether the effects of evaluation source on the reactions towards the feedback, organization and job were mediated by the reactions towards the procedure (see Figure 2).[2] To control for the covariance between reactions, we tested the indirect effects through multiple mediator models. Results showed that evaluation source had a negative indirect effect, via fairness perceptions, on feedback acceptance (IE = −.22, *SE* = .11, 95% CI = [−.47, −.05]), organizational attraction (IE = −.35, *SE* = .12, 95% CI = [−.60, −.13]) and job acceptance intentions (IE = −.32, *SE* = .14, 95% CI = [−.63, −.06]).

Discussion

Study 1 provides evidence that algorithm-based evaluations (vs. recruiter-based evaluations) can negatively affect applicant reactions, specifically fairness perceptions, perceived predictive validity, emotional creepiness and feedback acceptance. Furthermore, algorithm-based evaluations negatively affected feedback acceptance, organizational attraction and job acceptance intentions through their negative impact on fairness perceptions. Although selection decision favourability was the strongest predictor of applicant reactions, receiving a *positive decision* from an algorithm resulted in similar reactions in terms of fairness, face validity, predictive validity and emotional creepiness as receiving a *negative decision* from a recruiter. Thus, participants did not only care about the outcome of the procedure, they also cared about the procedure that is used to arrive at that outcome. In line with Acikgoz et al. (2020), we found no support for the moderating role of selection decision favourability, suggesting that the use of algorithm-based evaluations (vs. recruiter-based evaluations) has a similar (and mostly negative) effect on applicant reactions regardless of whether the selection decision is positive or negative.

[2]We are aware that the relations between our mediators and dependent variables might be attributable to additional causal variables (Spector, 2019), so the results of our mediation analyses should be interpreted with caution.

STUDY 2

The goal of Study 2 was to test Hypotheses 1, 2 and 3.

Materials and methods

Procedure

Data were again collected via Prolific, targeting native English-speaking participants living in the United States. We used a 4 (combined algorithm, verbal algorithm, nonverbal algorithm vs. recruiter) × 2 (positive vs. negative decision) between-subjects design, for which a power analysis (Faul et al., 2009) showed that the minimum required sample size of 179 is needed to have 80% power to detect a medium-sized effect (f = .25). We ceased participant recruitment after more than 500 participants completed the first part of the study. Apart from the payment (in this study $7 for part 1 and $2 for part 2) and the manipulation of the evaluation source, we used the same procedure as in Study 1.

We manipulated evaluation source through the decision letter. This letter was the same as in Study 1 apart from one additional paragraph with further details on the cues that had been used in the evaluation (Table 4). Participants were randomly assigned to one of our four conditions (recruiter, combined algorithm, verbal algorithm or nonverbal algorithm). To check whether our manipulations were successful, we used the same two manipulation checks as in Study 1. In case the participants indicated that they had been evaluated by an algorithm, we also asked them on which cues this algorithm was based (answer options: 'Verbal and nonverbal cues', 'Verbal cues only', 'Nonverbal cues only' and 'I don't know').

Participants

A total of 506 participants completed the AVI and the HEXACO-60, of which 445 also completed the second part of our study. We removed 36 cases because of a failed manipulation check of selection decision favourability, and 126 cases because of a failed manipulation check regarding the evaluation source (with n = 104 participants who failed to remember on which cues the algorithm was based). Furthermore, five cases were removed because of a failed attention check, and two cases because of either low or high variability in HEXACO-60 responses. Hence, our final sample consisted of 276 participants (28.3% men; 71.0% women; .7% other), of which 47 were rejected by the recruiter, 52 were accepted by the recruiter, 73 were rejected by one of the three algorithms (n = 26 for combined algorithm, n = 29 for verbal algorithm and n = 18 for nonverbal algorithm) and 104 were accepted by one of the three algorithms (n = 39 for combined algorithm, n = 36 for verbal algorithm and n = 29 for nonverbal algorithm). The number of participants across the three algorithm conditions ranged from 47 to 65. Participants' mean age was 32.45 years (SD = 12.54). On average, participants had 12.55 years of work experience (SD = 11.35) and they had applied for 13.40 (SD = 64.29) jobs in the last 2 years. Our final sample differed in terms of age (M = 32.45, SD = 12.54) from the participants who only completed the first part of our study (M = 29.57, SD = 9.48, t = −2.94, p < .01, d = .26), but did not differ in terms of gender, educational level, baseline measures of organizational attraction and job acceptance intentions, interest in the management traineeship and self-assessed performance on the AVI.

Measures

All variables were measured with the same items as in Study 1. The results showed that a model in which the seven factors were allowed to covary (χ^2[303] = 772.92, p < .01, TLI = .93, CFI = .94, RMSEA = .08,

TABLE 4 Additional paragraph to manipulate information source in Study 2.

	Recruiter condition	Combined algorithm condition	Nonverbal algorithm condition	Verbal algorithm condition
Details on information source in both the positive and negative selection decision favourability condition	Based on their knowledge and experience, our recruiters rate candidates' personality characteristics based on the interview recordings. When ratings these personality characteristics, our recruiters can choose to pay attention to, for example, what is said (verbal cues) as well as how things are said (nonverbal cues) by the candidate in response to each of the interview questions. Our recruiters then compare their own ratings of these personality characteristics to candidates' scores on the personality questionnaire to arrive at an overall rating	Using machine learning techniques, we developed an algorithm that extracts personality characteristics from interview recordings based on what is said (verbal cues) and how things are said (nonverbal cues). Examples of verbal cues are the topics that are discussed and the way these topics are described (e.g. words and word order in each sentence). Examples of nonverbal cues are facial expressions and vocal patterns (e.g. tone and pitch). These scores are then automatically combined with candidates' scores on the personality questionnaire	Using machine learning techniques, we developed an algorithm that extracts personality characteristics from interview recordings based solely on how things are said (nonverbal cues). Examples of nonverbal cues are facial expressions and vocal patterns (e.g. tone and pitch). These nonverbal algorithm scores are then automatically combined with candidates' scores on the personality questionnaire. Note that this algorithm does not take into account the content of what is said (verbal cues), such as the particular topics that are discussed during the interview	Using machine learning techniques, we developed an algorithm that extracts personality characteristics from interview recordings based solely on what is said (verbal cues). Examples of verbal cues are the topics that are discussed and the way these topics are described (e.g. words and word order in each sentence). These verbal algorithm scores are then automatically combined with candidates' scores on the personality questionnaire. Note that this algorithm does not take into account how things are said during the interview (nonverbal cues)

Note: The decision letter in Study 2 was the same as in Study 1 apart from this additional paragraph, which was presented after the introduction paragraph (see Table 1).

SRMR = .07), fit the data significantly better than a one-factor model ($\Delta\chi^2[21] = 2519.93$, $p < .01$, $\chi^2[324] = 3292.85$, $p < .01$, TLI = .59, CFI = .62, RMSEA = .18, SRMR = .10), or a three-factor model with the items measuring reactions towards the selection procedure, the feedback and the organization and job loading on separate factors ($\Delta\chi^2[18] = 1191.62$, $p < .01$, $\chi^2[321] = 1964.54$, $p < .01$, TLI = .77, CFI = .79, RMSEA = .14, SRMR = .09).

Results

Table 5 presents the descriptive statistics, alpha coefficients and correlations of all study variables. We report the analyses without control variables, unless controlling for these variables changed our findings (see Footnote 3).

Hypothesis testing

To test our hypotheses, we conducted a series of (M)AN(C)OVAs (Tables 6 and 7).

Applicant reactions towards the selection procedure

We found significant main effects for evaluation source (Wilk's $\lambda = .91$, $F[4, 269] = 6.79$, $p < .01$) and selection decision favourability (Wilk's $\lambda = .78$, $F[4, 269] = 18.52$, $p < .01$) in the expected directions, but no significant interaction effect (Wilk's $\lambda = .99$, $F[4, 269] = .92$, $p = .46$). Follow-up analyses revealed lower fairness perceptions ($F[1, 272] = 17.70$, $p < .01$, partial $\eta^2 = .06$) when participants were evaluated by an algorithm rather than a recruiter.[3] Thus, Hypothesis 1a was partially supported and Hypothesis 2 was rejected for reactions towards the selection procedure.

Applicant reactions towards the feedback

We found a significant main effect for selection decision favourability in the expected direction ($F[1, 272] = 62.16$, $p < .01$, partial $\eta^2 = .19$), but no effect for evaluation source ($F[1, 272] = .71$, $p = .40$, partial $\eta^2 < .01$), nor a significant interaction effect ($F[1, 272] = .33$, $p = .56$, partial $\eta^2 < .01$). Hence, Hypothesis 1b and Hypothesis 2 were rejected for feedback acceptance.

Applicant reactions towards the organization and the job

We found a nonsignificant main effect for evaluation source (Wilk's $\lambda = 1.00$, $F[2, 271] = .21$, $p = .81$), a significant main effect for selection decision favourability in the expected direction (Wilk's $\lambda = .76$, $F[2, 271] = 42.06$, $p < .01$) and a nonsignificant interaction effect (Wilk's $\lambda = .99$, $F[2, 271] = .72$, $p = .49$). Thus, Hypothesis 1c and Hypotheses 2 were rejected for reactions towards the organization and the job.

Applicant reactions to different algorithm sources

When comparing the three different algorithm conditions to each other, we found no significant differences in applicant reactions based on the algorithm's information source. However, when comparing all four conditions (including the recruiter condition) to each other, we found a significant effect of evaluation source on fairness perceptions, Wilk's $\lambda = .90$, $F[3, 272] = 4.39$, $p < .01$. A post hoc Bonferroni test revealed that fairness perceptions were significantly lower in the nonverbal algorithm condition ($M = 3.76$, $SD = 1.64$) than in the recruiter condition ($M = 4.73$, $SD = 1.70$), $M_{\text{diff}} = .97$, $SE = .30$, $p < .01$, CI = (.18, 1.77), $d = .58$. There were no other significant differences across the four conditions. In short, we found no support for Hypothesis 3.

[3]When controlling for self-assessed performance and interest in the position, we also found lower perceived predictive validity ($F[1, 270] = 3.88$, $p = .0498$, partial $\eta^2 = .01$) for algorithm-based evaluations as opposed to recruiter-based evaluations.

TABLE 5 Means, standard deviations and correlations between study variables (Study 2).

	M	*SD*	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Demographics																	
1. Age	32.45	12.54	–														
2. Gender	.73	.49	−.23**	–													
Pre-decision reactions T0																	
3. Self-assessed performance	4.08	1.33	.02	−.09	(.84)												
4. Interest in the job	5.08	1.54	.15*	−.15*	.25**	–											
5. Organizational attraction	5.30	1.20	.09	−.08	.28**	.70**	(.95)										
6. Job acceptance intentions	5.49	1.21	.02	.00	.13*	.59**	.62**	(.76)									
Manipulations																	
7. Evaluation source	.64	.48	.01	.08	.06	.00	.05	−.04	–								
8. Selection decision favourability	.57	.50	.04	.03	.21**	.24**	.24**	.11	.06	–							
Post-decision reactions T1																	
9. Fairness perceptions	4.28	1.71	−.01	−.10	.17**	.31**	.32**	.14*	−.20**	.43**	(.96)						
10. Face validity	4.80	1.38	−.01	−.06	.18*	.29**	.31**	.18*	−.01	.29**	.65**	(.92)					
11. Perceived predictive validity	3.74	1.50	.03	−.18**	.21**	.31**	.38**	.21**	−.09	.40**	.80**	.68**	(.90)				
12. Emotional creepiness	3.19	1.35	−.09	.12*	−.23**	−.35**	−.37**	−.22*	.03	−.37**	−.58**	−.63**	−.55**	(.85)			
13. Feedback acceptance	4.72	1.56	−.03	.01	.09	.21**	.26**	.14*	−.02	.44**	.69**	.59**	.67**	−.51**	(.89)		
14. Organizational attraction	4.24	1.66	−.02	−.06	.21**	.45**	.52**	.35**	.02	.50**	.64**	.53**	.66**	−.52**	.54**	(.97)	
15. Job acceptance intentions	4.54	1.70	−.05	−.02	.19**	.39**	.44**	.40**	.04	.41**	.52**	.40**	.51**	−.37**	.47**	.79**	(.92)

Note: $N = 276$. Gender is coded as 0 = man and 1 = woman. Evaluation source is coded as 0 = recruiter and 1 = algorithm. Selection decision favourability is coded as 0 = negative and 1 = positive. All other variables were measured on a 7-point scale. Alpha coefficients are presented on the diagonal. $^{**}p < .01$. $^{*}p < .05$ (two-tailed).

TABLE 6 Descriptive statistics and between-subjects tests for recruiter versus algorithm (Study 2).

	Overall, *M* (*SD*)	Negative decision, *M* (*SD*)	Positive decision, *M* (*SD*)	*F* (partial η^2) Evaluation source	Selection decision favourability	Interaction effect
Fairness perceptions				17.70** (.06)	63.46** (.19)	.00 (.00)
Recruiter	4.73 (1.70)	3.93 (1.77)	5.46 (1.26)			
Algorithm	4.02 (1.67)	3.14 (1.48)	4.64 (1.51)			
Face validity				.09 (.00)	25.88** (.09)	1.47 (.01)
Recruiter	4.81 (1.39)	4.26 (1.28)	5.31 (1.30)			
Algorithm	4.79 (1.37)	4.41 (1.33)	5.06 (1.34)			
Perceived predictive validity				3.78 (.01)	40.41** (.13)	.59 (.00)
Recruiter	3.92 (1.54)	3.19 (1.46)	4.58 (1.30)			
Algorithm	3.64 (1.48)	2.98 (1.36)	4.11 (1.38)			
Emotional creepiness				1.08 (.00)	17.70** (.06)	.05 (.00)
Recruiter	3.13 (1.25)	3.64 (1.14)	2.66 (1.17)			
Algorithm	3.22 (1.41)	3.84 (1.34)	2.79 (1.29)			
Feedback acceptance				.71 (.00)	62.16** (.19)	.33 (.00)
Recruiter	4.77 (1.69)	3.98 (1.77)	5.48 (1.25)			
Algorithm	4.69 (1.48)	3.93 (1.54)	5.23 (1.18)			
Organizational attraction				.07 (.00)	84.40** (.24)	.01 (.00)
Recruiter	4.20 (1.66)	3.33 (1.51)	4.99 (1.36)			
Algorithm	4.26 (1.67)	3.26 (1.56)	4.96 (1.38)			
Job acceptance intentions				.04 (.00)	48.39** (.15)	.72 (.00)
Recruiter	4.45 (1.73)	3.82 (1.68)	5.02 (1.59)			
Algorithm	4.59 (1.69)	3.69 (1.67)	5.23 (1.40)			

Note: $N = 276$, with n per cell varying between 47 and 104. All variables were measured on a 7-point scale. Evaluation source is coded as 0 = recruiter and 1 = algorithm. Selection decision favourability refers to the valence of the selection decision and is coded as 0 = negative and 1 = positive. **$p < .01$. *$p < .05$.

Exploratory analyses

We again explored whether the effects of evaluation source on reactions towards the feedback, the organization and the job were mediated by the reactions towards the procedure. We found a negative indirect effect of evaluation source on feedback acceptance (IE = −.24, *SE* = .09, 95% CI = [−.44, −.08]), organizational attraction (IE = −.20, *SE* = .08, 95% CI = [−.37, −.06]) and job acceptance intentions (IE = −.14, *SE* = .06, 95% CI = [−.26, −.04]) via fairness perceptions (see Figure 2).

Discussion

Study 2 provides further evidence that algorithm-based evaluations (vs. recruiter-based evaluations) can negatively affect applicant reactions, specifically fairness perceptions and perceived predictive validity. Again, the strongest and most consistent predictor of applicant reactions was selection decision favourability. Furthermore, as in Study 1, algorithm-based evaluations negatively affected

TABLE 7 Descriptive statistics and between-subjects tests for the different evaluation source conditions (Study 2).

	Evaluation source						
	Recruiter	Algorithm − combined	Algorithm − verbal	Algorithm − nonverbal			
	M (*SD*)	*M* (*SD*)	*M* (*SD*)	*M* (*SD*)	*F*	*p*	Partial η^2
Fairness perceptions	4.73 (1.70)[a]	4.20 (1.82)	4.04 (1.53)	3.76 (1.64)[a]	4.39	.00	.05
Face validity	4.81 (1.39)	4.81 (1.56)	4.81 (1.21)	4.75 (1.34)	.02	.99	.00
Perceived predictive validity	3.92 (1.54)	3.77 (1.66)	3.56 (1.33)	3.74 (1.50)	.96	.41	.01
Emotional creepiness	3.13 (1.25)	3.16 (1.52)	3.38 (1.29)	3.19 (1.35)	.61	.61	.01
Feedback acceptance	4.77 (1.69)	4.60 (1.66)	4.67 (1.25)	4.85 (1.53)	.27	.85	.00
Organizational attraction	4.20 (1.66)	4.49 (1.75)	4.09 (1.54)	4.18 (1.75)	.69	.56	.01
Job acceptance intentions	4.45 (1.73)	4.65 (1.81)	4.48 (1.62)	4.66 (1.63)	.29	.84	.00

Note: $N = 276$, with n per cell varying between 47 and 99. All variables were measured on a 7-point scale.

[a]Evaluation sources with the same letter differ significantly from one another.

reactions towards the feedback, organization and job through their negative impact on fairness perceptions. As in Study 1, we found no support for the moderating role of selection decision favourability.

We also examined how the use of different information sources (i.e. verbal vs. nonverbal cues) affects applicant reactions to algorithm-based evaluations. Surprisingly, participants did not react differently depending on the information source. In fact, a large number of participants had trouble remembering which cues had been used to arrive at the selection decision (i.e. $n = 104$ participants failed this manipulation check and had to be removed from the data set), indicating that participants may not care about the specific type of cue that is used in an algorithm. An alternative explanation could be that participants are less motivated to read or remember detailed information about information sources in a hypothetical application process as they would be in a high-stakes context.

An interesting finding worth further investigation is that we found fewer direct effects of evaluation source on applicant reactions in Study 2. A closer inspection of Tables 3 and 6 shows that especially the applicant reactions towards the negative decision made by the recruiter were lower in Study 2 than in Study 1. An important difference between the two studies is that the decision letter in Study 2 specified that recruiters can choose to pay attention to both verbal cues and nonverbal cues in response to each interview question. Thus, although information source did not affect applicant reactions to algorithm-based evaluations, it could be that information source affects reactions towards recruiter-based evaluations, particularly when the selection decision is negative.

GENERAL DISCUSSION

Our goal was to examine applicant reactions to the use of algorithm-based (vs. recruiter-based) evaluations to make initial screening decisions. Overall, our results showed several negative applicant reactions to the use of algorithms. Specifically, in Study 1, informing participants that an algorithm had been used to analyse their AVI and personality inventory lowered fairness perceptions, perceived predictive validity and feedback acceptance and increased emotional creepiness. We were able to replicate these effects for fairness perceptions and for perceived predictive validity (when controlling for self-assessed performance and interest in the position) in Study 2. In contrast with our hypotheses, applicant reactions were not significantly affected by the interaction between evaluation source and selection decision favourability. Furthermore, we found some tentative evidence that applicant reactions to algorithm-based evaluations are not affected by the type of information source (i.e. verbal vs. nonverbal cues) on which the algorithm is based.

Theoretical implications

First, the present study advances the external validity of research on the use of new technology in selection (Woods et al., 2020) by examining applicant reactions to algorithm-based evaluations after participants have experienced the selection procedure first-hand *and* after they have been informed about the selection decision. In earlier studies, applicants reported their reactions based on vignettes (Acikgoz et al., 2020; Langer et al., 2021; Mirowska, 2020; Wesche & Sonderegger, 2021) and without being aware of the final selection decision (for an exception, see Acikgoz et al., 2020). As post-decision reactions are more strongly related to long-term attitudes and behaviours than pre-decision reactions (Hausknecht et al., 2004), post-decision reactions are worth paying attention to from an organizational perspective. These reactions are particularly important if organizations do not want to run the risk of losing highly-qualified applicants to competitors in late selection stages and care about starting off the employment relationship on the right foot (Konradt et al., 2017).

Compared to previous studies on applicant reactions to algorithm-based evaluations, our study provides several novel insights. Importantly, we show that decision favourability is a much stronger predictor of applicant reactions to algorithm-based evaluations than previously thought: where Acikgoz et al. (2020) reported an average correlation of .06 between decision favourability and applicant reactions (after reverse coding litigation intentions), we found an average correlation of .34 (after reverse coding emotional creepiness). These findings show that hypothetical decisions based on vignettes do not cause the same reactions as experiencing the selection procedure first-hand and receiving a decision based on one's actual personality scores. Obviously, the strong main effect of decision favourability leaves less variance in applicant reactions to be explained by evaluation source, which can explain why we found less consistent applicant reactions to algorithm-based evaluations than previous studies. As high-stakes selection contexts are likely to cause even stronger reactions to decision favourability, we believe vignette studies may *underestimate* the effects of decision favourability and *overestimate* the effects of evaluation source. Furthermore, our results showed that the fairness of the procedure is applicants' most focal concern when being evaluated by an algorithm. Importantly, although we did not formulate specific hypotheses about these effects, it is through fairness perceptions that the use of algorithm-based evaluations influence reactions towards the feedback, the organization and the job. Hence, future studies should ensure to include fairness perceptions when examining applicant reactions to algorithm-based evaluations. Finally, we contribute to Acikgoz et al.'s (2020) findings by including two additional applicant reactions that are especially relevant when examining applicant reactions to algorithm-based after informing participants of the selection decision: emotional creepiness and feedback acceptance. We found some evidence that algorithm-based evaluations may also increase emotional creepiness (Study 1, but not Study 2) and decrease feedback acceptance through fairness perceptions (Studies 1 and 2).

Second, we expand the theoretical lens of research on applicant reactions to algorithm-based evaluations by introducing two theoretical frameworks to this field: SET (Blau, 1964; McClintock et al., 1984) and the AART (Ployhart & Harold, 2004). Thus far, research on applicant reactions to algorithm-based evaluations relied on Gilliland's (1993) justice model and signalling theory (Bangerter et al., 2012; Spence, 1973). As applicant reactions research has moved beyond Gilliland's model (McCarthy et al., 2017), we considered it important to show that more recent theoretical frameworks in this field yield similar predictions about the effects of algorithm-based evaluations. Apart from signalling theory, these theories also suggest that rejected applicants show the strongest negative reactions to algorithm-based evaluations. However, in contrast to our expectations, applicants reacted more negatively to algorithm-based evaluations (vs. recruiter-based evaluations) independent of whether the decision was positive or negative. Thus, a negative evaluation by an algorithm seems to pose a comparable violation of justice rules (Gilliland, 1993), reciprocity violation (Gouldner, 1960), or threat to applicants' self-esteem (Ployhart & Harold, 2004) as a negative evaluation by a recruiter. As decision favourability is a central component of the AART, our findings have important implications for this theory in particular. Self-serving attributions are not only triggered when situations are unfavourable but also when they are surprising or novel (Wong & Weiner, 1981). According to Ployhart and Harold (2004), the use of technology is one of these triggers, and a lack of real contact with an organizational representative may by another trigger. Although algorithms are one of the most novel selection technologies, our study suggests that their use does not make applicants more likely to attribute a negative decision to the selection procedure. Hence, the role of novel or surprising events, and particularly the use of technology, in applicant attribution processes may be smaller than the AART suggests. However, it is important to replicate these findings in an actual selection setting, in which selection decisions have more critical consequences.

Third, there have been several calls to examine whether applicants react differently to the use of incidental information, over which they have little control, versus information that they provide intentionally (Oswald, 2020; Tippins et al., 2021). Hence, the present study has provided new insights to the literature by suggesting that the use of controllable information (i.e. verbal cues) may lead to similar applicant reactions as the use of incidental data (i.e. nonverbal cues) or a combination of the two types of information (i.e. verbal and nonverbal cues). One explanation might be that our manipulations caused two opposing effects that cancelled each other out: On the one hand, we emphasized the use of uncontrollable information in the nonverbal and combined conditions, which should reduce applicant reactions in general, and affective reactions like emotional creepiness in particular (Langer et al., 2018; Tene & Polonetsky, 2015). On the other hand, in all four conditions, we also provided more information on the procedure, which could have led to less uncertainty, and therefore more positive applicant reactions (Truxillo et al., 2009). A second explanation could be that applicants already assumed that nonverbal cues are being evaluated in interviews, which made the additional information about the use of nonverbal cues unsurprising. Indeed, a recent meta-analysis by Martín-Raugh et al. (2022) showed that, depending on cue type, nonverbal cues explain between 2 and 38% of the variance in interview evaluations. A final explanation could be that applicants care more about the exact verbal cues (e.g. the number of competency-related words vs. the number of prepositions) or nonverbal cues (e.g. enthusiastic facial expressions vs. specific facial features) that are being used in the algorithm than the mere fact that these cues are being used.

Practical implications

Overall, the present study found some negative applicant reactions to the use of algorithms and—importantly—no positive effects at all. Hence, it might be difficult for organizations to reap the benefits of algorithm-based evaluations as unfavourable applicant reactions can damage their image and reputation (Steiner, 2017) and negatively impact employees' work attitudes and behaviours (McCarthy et al., 2017). To prevent legal complaints, several organizations have already decided to cease the use of paraverbal and nonverbal cues in their algorithms (Kahn, 2021). However, based on our tentative findings, excluding these cues might not make applicants react more positively towards the use of algorithms. Organizations that are concerned with these negative consequences, might consider relying on human judgements rather than algorithms in their selection procedures. However, to ensure the validity of selection procedures, human judgements should not be intuitive, but based on standardized procedures and decision rules (Kuncel et al., 2013). Furthermore, Basch and Melchers (2019) showed that applicant reactions to new technology may be improved by using explanations that emphasize standardization and flexibility. Thus, if organizations use algorithm-based evaluations, they might be able to attenuate or prevent negative reactions by explaining and emphasizing the increased standardization and validity of algorithms beforehand.

Limitations and suggestions for future research

The present study has five limitations that should be noted. First, the present study did not take place in an actual high-stakes selection context. We believe that, at this point, it would not have been ethical to test our hypotheses among an actual applicant sample, as scientific evidence for the validity of AVIs, especially in combination with algorithm-based evaluations, is currently lacking. Furthermore, in a high-stakes context, it would have been unfair to randomly assign participants to different conditions. Therefore, it remains to be shown whether our results can be generalized to applicant samples.

Second, our study does not provide insights into the underlying reasons why applicants react negatively to algorithm-based evaluations. Applicants may react more negatively to algorithms because they violate justice rules (Gilliland, 1993), send signals that the organization does not value human contact (Mirowska & Mesnet, 2022) or violate reciprocity norms (Gouldner, 1960). Moreover, these underlying mechanisms may differ per selection tool. In the present study, we focused on a selection procedure consisting of two often-used pre-screening methods (Basch et al., 2022). However, it could be that algorithms violate different justice rules or send different signals when they are used to score an AVI compared to when they are used to score a personality inventory. Future research is therefore needed to test the exact underlying mechanisms for different selection tools, which may guide the development of effective interventions. We would also like to note that the use of algorithm-based evaluations is growing and expectations and attitudes regarding their use may change in the future.

Third, our studies are limited in *when* the use of algorithms was presented. In many countries, it is common to explain how (automated) scores are calculated to applicants *after* rather than *before* participants have completed the selection procedure. However, artificial intelligence legislation differs per country. Indeed, some of the first legislation specifically on artificial intelligence in personnel selection, such as the Artificial Intelligence Video Interview Act (Illinois General Assembly, 2019), states that organizations should explain how artificial intelligence works before applicants start the selection procedure. Applicants might react differently to the use of algorithm-based evaluations depending on the time of information provision. For example, knowing beforehand that AVI responses will be evaluated by an algorithm rather than a recruiter might influence pre-test reactions, which may influence subsequent performance on the AVI and cause even stronger negative post-test reactions (Proost et al., 2021). Future research is therefore needed to examine the generalizability of our findings to the various other moments applicants can be informed about the use of algorithms.

Fourth, our studies are also limited in *how* the use of algorithms was presented. Different wording of our manipulations of evaluation source may produce different effects. When creating our manipulations, we not only focused on the external validity but also on the internal validity of our study design. Consequently, we kept the wording in the different conditions as similar as possible, which may have caused an unnatural emphasis on certain aspects of the selection procedure (e.g. the human touch in the recruiter-based evaluation). As different wording of explanations could produce differences in perceptions (Langer et al., 2021), more research on explanations of algorithm-based evaluations is needed to establish the generalizability of our results.

Finally, compared to Study 1, the algorithm conditions in Study 2 differed in two ways: the decision letters specified the exact cues on which the algorithm was based *and* the fact that a machine-learning algorithm was used. Although machine-learning algorithms are often employed to score AVIs (Lukacik et al., 2022), participants in Study 1 may have had a simpler algorithm in mind while completing the applicant-reaction measures. Nevertheless, Study 2 largely replicated our findings in Study 1.

CONCLUSION

Rapid advancements in digital technologies have led to the emergence of algorithm-based evaluations to aid selection decisions. These automated evaluations are used to speed up and objectify certain parts of the selection procedure, but also come with some potential downsides and risks. The present study zooms in on one such potential downside: negative applicant reactions. Indeed, the present study indicates that applicants show unfavourable reactions to the use of algorithm-based evaluations. These negative effects of algorithm-based evaluations (vs. recruiter-based evaluations) on applicant reactions are independent of the selection decision. Considering the current labour market, in which it is difficult to attract and retain applicants, organizations should carefully consider whether the benefits of using algorithms outweigh its downsides.

AUTHOR CONTRIBUTIONS

Janneke K. Oostrom: Conceptualization; data curation; formal analysis; funding acquisition; investigation; methodology; project administration; validation; visualization; writing – original draft; writing – review and editing. **Djurre Holtrop:** Conceptualization; methodology; writing – original draft. **Antonis Koutsoumpis:** Conceptualization; methodology; writing – original draft. **Ward van Breda:** Conceptualization; methodology; writing – original draft. **Sina Ghassemi:** Conceptualization; methodology; writing – original draft. **Reinout E. de Vries:** Conceptualization; methodology; writing – original draft.

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflict of interest.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available on the Open Science Framework (https://osf.io/54vzx/?view_only=c861e6c85bc245fd8c9c6fcbb3f1b33a).

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