Abstract

The purpose of this study was to investigate the effects of using artificial intelligence in selection on applicant reactions. Utilizing a 2x2 experimental design (N = 320), findings indicated that participants had significantly more negative reactions in terms of organizational attraction, perceptions of justice, and litigation intentions when AI was the decision-maker compared to the human condition. Findings from this study may help inform organizations regarding what selection procedures to utilize in order to attract and retain top talent.

With organizations increasingly recognizing the importance of human capital, applying the right approach to staffing has emerged as a key factor influencing organizational effectiveness. Recruiting the right talent is now seen as a crucial aspect of competitive advantage as it determines whether an organization has the pool of knowledge, skills, abilities, and other characteristics needed for survival and success (Phillips & Gully, 2015). While recruiting is generally thought of as the initial stage of staffing in which organizations seek to attract a large number of potential applicants, those actions by organizations that influence whether individuals who initially apply will stay in the applicant pool and eventually accept a job offer are also important stages in the recruitment process (Barber, 1998). What this implies is that for a recruitment effort to be successful, equally as important as the effectiveness of the initial communication channels is whether the targeted individuals have favorable reactions to the way they are treated by the organization during the process (Walker, Bauer, Cole, Bernerth, Field, Short, 2013).

Applicant reactions refers to attitudes, affect, or cognitions applicants might have about a hiring process (Ryan & Ployhart, 2000). Contrary to the traditional staffing literature, which examines the issue from the organizational perspective and is concerned about the validity and utility of selection decisions, applicant reactions research has approached the issue from the applicants' perspective as selection in this context actually occurs both ways (Hausknecht, Day, & Thomas, 2004). Initially based on the organizational justice framework (Gilliland, 1993), multiple conceptualizations of applicant reactions have been developed. Generally, these models conceptualize applicant reactions as consisting of procedural and distributive justice perceptions, attitudes and motivation towards test, and test anxiety (Hausknecht et al., 2004; McCarthy, Bauer, Truxillo, Anderson, Costa, & Ahmed, 2017). Several factors have been proposed to influence applicant reactions, including personal characteristics such as personality, values, and test experience, invasion of privacy during the process, transparency and length of the process, attractiveness of the job and the organization, type and content of the test, and even societal norms (Hausknecht et al., 2004; McCarthy et al., 2017).

In fact, there is a large body of literature examining antecedents and consequences of applicant reactions to organizational staffing practices (McCarthy et al., 2017). There is evidence suggesting that applicant reactions influence important outcomes such as motivation during the selection process, organizational attractiveness (Hausknecht et al., 2004), and even job performance (McCarthy, Van Iddekinge, Lievens, Kung, Sinar, & Campion, 2013). However, with technology advancing at a mind-blowing pace, practitioners are embracing new methods in recruitment and selection without enough research scrutiny. For example, with advanced technologies such as resume screening and interview assessments by artificial intelligence (AI) allowing companies to process large numbers of applications and helping recruiters save time and money, more organizations are embracing this as a tool in staffing (Alsever, 2017; Florentine, 2017). Despite this popularity, research has yet to examine whether applicants have favorable reactions to an increased involvement of AI in the selection process.

An increased involvement by AI in the staffing process naturally means less human interaction for applicants. Accordingly, two processes might be operating in shaping applicants' reactions. First, applicants may view staffing by AI favorably as they may believe that AI would lack human subjectivity and make better hiring decisions. Second, applicants may believe that less human interaction means the organizations do not value them and thus may have unfavorable reactions. In other words, while it can be argued that these tools lack human subjectivity and thus would be viewed favorably by applicants in terms of justice perceptions, it is also possible that lack of human involvement may signal to prospective employees that they are not valued by the organization and thus lead to negative applicant reactions. Accordingly, the purpose of this study is examining whether applicants have positive reactions toward the use of artificial intelligence in selection decisions. Through an experimental design, this study investigates the extent to which procedural and distributive justice perceptions are influenced by whether or not AI was utilized in making hiring decisions, which in turn is expected to predict a number of applicant reaction outcomes including organizational attraction, job pursuit intentions, intentions to recommend the organization to others, and intentions to seek legal action against the organization. The moderating effects by favorability of the selection outcome and self-efficacy with using computers are also examined (see Figure-1). By doing so, this study also responds to recent calls for research to examine the effect of incorporation of new technology on applicant reactions (McCarthy et al., 2017) and reactions to the automatic evaluation of digital interviews (Langer, König, & Krause, 2017). However, before examining the issue in more detail, we now proceed to a brief description of what AI is and how it is used in staffing by organizations.

Artificial Intelligence in Staffing

Artificial intelligence can roughly be defined as intelligence displayed by machines, as opposed to biological intelligence observed in humans and animals (Wikipedia, 2018). While it is frequently used interchangeably, it is a different and broader concept than machine learning, which refers to the process by which large amounts of data are supplied to a machine with the goal of letting it learn by itself (Marr, 2016). Machines accomplish this through neural networks, which are algorithms designed to recognize patterns in data by classifying information like human brain. For example, by utilizing a set of data containing images of human faces and associated emotions, the algorithm can learn to recognize emotions in humans it “sees”, and a feedback loop informing the machine whether it is accurate allows the algorithm to improve recognition over time. Similarly, a large number of written communications can be fed into an algorithm containing either a complaint or a compliment, and the machine can learn to “read” the message in a text and determine whether it is positive or negative (Marr, 2016). This is generally accomplished through natural language processing, a type of machine learning which is aimed at teaching a machine to understand the meaning of a piece of communication. In other words, the goal is teaching computers to understand and manipulate human language in text or speech format to perform desired tasks (Chowdhury, 2003).

Machine learning techniques are being utilized by hiring professionals through a number of start-ups that offer such services. For example, the software developed by one company utilizes data from interviews and examines certain characteristics of a candidate’s speech such as a preference for specific words and pace of speech, with the goal of constructing a psychological profile and using it to predict whether an individual will fit a company’s culture (Alsever, 2017). Other services provided by such start-ups include mining the social media posts and other publicly available data on the internet in order to predict whether they will switch jobs or engage in other counterproductive work behaviors, or utilizing video interviews to examine characteristics of an applicant’s voice and gestures to make predictions about the applicant’s credibility. Using active verbs such as “can” or “will” vs. words with negative connotations such as “can’t” or “have to”, a change in vocal tone while saying a certain word, or even slight changes in facial expressions difficult to be caught by humans while responding to a question are all used by the algorithm as inputs in making an overall evaluation of a candidate (Alsever, 2017). Large corporations are also developing their own AI software to comb through a large number of applicants and make decisions regarding whether to reject the application outright or allow it to proceed to the next hurdle (Alsever, 2017).

While it is possible that these applications result in better hiring decisions by minimizing human bias in the process, whether applicants view this to be the case and have positive reactions towards delegation of hiring decisions by organizations to AI is yet to be examined. This is an important omission in the literature given the common finding that applicant reactions to selection practices predict a number of important outcomes (McCarthy al., 2017). For example, in a meta-analytic investigation, Hausknecht et al. (2004) found that applicant reactions to selection procedures including procedural and distributive justice perceptions, test anxiety and motivation, and attitude towards selection and tests predicted a number of important outcomes including performance in the selection procedures, organizational attractiveness, intentions to recommend the organization to others, and intentions to accept a job offer. In a more recent meta-analysis, Anderson, Salgado, and Hulsheger (2010) found that these reactions were not situationally specific but generalized across selection contexts and even countries. Given these important outcomes, it is essential to understand whether applicant have favorable perceptions of the use of AI in selection.

Applicant Reactions to AI

Given the focal position justice perceptions hold in applicant reactions models (e.g., McCarthy et al., 2017), reactions to AI in selection can also be examined from an organizational justice perspective. Organizational justice, or fairness, has been conceptualized in different ways by researchers. While early theory focused on fairness of the outcomes of decisions made by organizational agents, termed distributive justice, later work has examined the process through which the decisions are made, namely procedural justice (Colquitt, 2001). Procedural justice has later been detailed by focusing on the quality of interpersonal treatment people receive during the procedures. Specifically, Greenberg (1990) argued that those aspects of procedural justice that pertain to the extent to which people are treated with politeness and respect could be called interpersonal justice, while the second type, labeled informational justice, encompassed the degree to which people are provided with explanations regarding why procedures were applied in a certain way. Most studies using an organizational justice framework in examining applicant reactions have utilized the model outlined by Gilliland (1993), which suggests that evaluations of procedural justice in a selection context encompass job relatedness of the procedure, opportunity to perform, reconsideration opportunity, consistency or administration, feedback, provision of justification for a decision, honesty, interpersonal effectiveness of the administrator, two-way communication, and propriety of questions asked during selection. Organizational justice has been found to predict important organizational criteria such as job satisfaction, organizational commitment, organizational citizenship behaviors, withdrawal, and job performance (Colquitt, Conlon, Wesson, Porter, & Ng, 2001).

From an organizational justice perspective, there are two opposing theoretical viewpoints that could influence the reactions applicants are likely to have regarding an increased involvement of AI in selection decisions. First, given their lack of subjectivity, applicants may view AI systems as being impartial and unbiased agents in making employment decisions. Accordingly, they may trust AI more than they trust humans in making selection decisions and thus have positive reactions to the use of AI in selection. Trust can be defined as a willingness to be vulnerable to the actions of another with the knowledge that the other party will perform a certain action regardless of whether it is being monitored (Mayer, Davis, & Schoorman, 1995). Mayer and colleagues propose that three characteristics are influential in influencing perceptions of trustworthiness: ability or expertise in the area, lack of an egocentric motive (i.e., benevolence), and following some set of principles in making decisions (i.e., integrity). Within this framework, AI may be perceived to be high in trustworthiness given its potentially very high level of expertise, lack of a specific motive or bias, and standardized decision-making procedures. While as a result of the process by which algorithms "learn", there is a possibility that AI may still be biased despite all the apparent standardization in the decision-making process (Dickey, 2017), in theory machine learning algorithms have the potential to be much less biased and more objective than the average human, which may lead applicants to perceive them favorably.

On the other hand, given the lack of or limited amount of human contact that follows an increased involvement of AI in selection, applicants may have unfavorable reactions as a result of potentially compromised interpersonal justice perceptions. Given the interpersonal aspects of procedural justice (Gilliland, 1993), it is possible that a lack of human interaction will lead to decreased feelings of procedural justice. According to Greenberg (1990), procedural justice judgments are influenced by the interpersonal treatment people receive from decision-makers (interpersonal justice) and the transparency in which decisions are made (informational justice). The interpersonal treatment facet of procedural justice refers to interpersonal effectiveness of the test administrator and includes the extent to which applicants are treated with warmth and respect (Gilliland, 1993). In fact, there is evidence suggesting that applicants generally have less favorable reactions to less personal selection procedures. Specifically, in a field study comparing applicant reactions to face-to-face vs. technology mediated interviews, Chapman, Uggerslev, and Webster (2003) found that face-to-face interviews were perceived to be more fair and were associated with higher job acceptance intentions compared to videoconferencing and telephone interviews. In a more recent study, Langer, König, and Krause (2017) examined applicant reactions to digital interviews in which applicants digitally record their answers, which are then scored by company representatives asynchronously. These authors found that digital interviews were perceived to be allowing for less two-way communication and providing worse interpersonal treatment compared to videoconference interviews.

The informational facet, on the other hand, refers to whether specific and adequate explanations were provided in a timely manner regarding the procedures applied in selection (Shapiro, Buttner, & Barry, 1994). There is evidence in support of the argument that a lack of transparency in selection process and decisions is associated with less favorable applicant reactions. Specifically, Truxillo, Bauer, Campion, & Paronto (2002) found that when given information about the job relatedness of a video testing procedure, police officer candidates had higher perceptions of fairness compared to those who weren't given the information. In addition, in a meta-analytic review, it was found that providing applicants with explanations regarding the procedure and outcomes was positively related with fairness perceptions, organizational attraction, test-taking motivation, and performance on a cognitive ability test (Truxillo, Bodner, Bertolino, Bauer, & Yonce, 2009). Given the way in which AI is utilized in selection decisions by many organizations (Alsever, 2017), these findings may actually suggest that applicants may have negative reactions to the use of AI in selection. Specifically, because of its highly technical nature, it is unlikely that organizations are able to provide a satisfying explanation of how a machine learning algorithm evaluates applicants' performances on a selection test and makes recommendations, which may lead to low levels of informational justice perceptions.

In sum, while perceptions of a lack of bias may potentially give rise to positive perceptions of procedural justice when AI is used in selection decisions, two other factors, namely inadequate selection information and interpersonal effectiveness, may elicit negative process fairness perceptions from applicants. Accordingly, instead of forming a hypothesis, we ask the following research question:

Research Question 1: Is the use of AI in making selection decisions associated with perceptions of procedural justice?

There is substantial evidence supporting the argument that as a selection procedure is perceived to be fair, applicants will have more positive reactions (Celani, Deutsch-Salamon, & Singh, 2008). For example, Schinkel, van Vianen, and Ryan (2016) found that perceptions of procedural fairness were significantly related to organizational attractiveness and intentions to recommend the organization to others. Similarly, Ababneh, Hackett, and Schat (2014) found that procedural fairness perceptions were positively associated with organizational attraction and recommendation intentions and negatively associated with intentions to litigate. In another study, Ployhart and Ryan (1997) found that perceptions of process fairness predicted recommendation, application, and acceptance intentions in a sample of graduate school applicants both before and after submitting their applications. These findings suggest that to the extent that applicants perceive AI algorithms to be impartial and unbiased and thus have positive procedural justice perceptions, they will have positive reactions towards using AI in selection. As four important outcomes of applicant reactions, this study examined organizational attraction, job acceptance intentions, recommendation intentions, and litigation intentions (McCarthy et al., 2017). Accordingly, the following is hypothesized:

Hypothesis 1: There will be a positive relationship between perceptions of procedural justice and a) attraction to the organization , b) job acceptance intentions, and c) recommendation intentions.

Hypothesis 2: There will be a negative relationship between perceptions of procedural justice and litigation intentions.

The process described above, namely a relationship between AI use and perceived procedural justice with procedural justice perceptions predicting applicant reaction outcomes, suggests that there might be a mediation effect such that the use of AI influences applicant reactions through procedural justice perceptions. In order to examine this possibility, the following research question is proposed:

Research Question 2: Is there a mediation between the use of AI in selection and applicant reactions through procedural justice perceptions?

As previously explained, distributive justice is another important dimension of justice perceptions with important implications for organizations. In their meta-analysis, Colquitt and colleagues found positive and strong correlations between distributive justice and outcome satisfaction, job satisfaction, organizational commitment, trust, and withdrawal behaviors (Colquitt et al., 2001). Gilliland (1993) includes distributive justice rules as another factor that may influence applicant reactions to selection procedures, which he defines as whether or not applicants receive the outcome they feel they deserve. In his model, equity and equality are proposed as two important rules that influence perceptions of distributive justice. Equity refers to the expectation that people should receive rewards in accordance with their inputs compared to an external standard. In the context of selection decisions, since applicants do not generally have a chance to compare their performance to that of other applicants' in determining equity, an internal standard based on past experiences is used regarding expectations of performance in a selection test (Gilliland, 1993). However, in the case of using AI to make selection decisions, it is likely that an applicant would not be able to draw upon his or her past experiences given the lack of similar experiences in the past stemming from the novelty of the situation. This may lead to lower levels of perceived distributive justice when AI is used regardless of the actual outcome. On the other hand, from an equality perspective, reactions to AI use may be favorable since it may be seen as an unbiased and impartial decision-maker. Equality rule implies that job-irrelevant characteristics such as race or gender are not used in making hiring decisions, and applicants may view AI in a positive light in this regard. Accordingly, since two separate distributive justice rules suggest opposing outcomes in terms of the relationship between AI use and distributive justice perceptions, the following research question is proposed:

Research Question 3: Is the use of AI in selection decisions associated with perceptions of distributive justice?

It is likely that perceived distributive justice will predict applicant reaction outcomes. For example, Hauksnecht et al. (2004) found that distributive justice perceptions were positively related to performance on selection tests, organizational attractiveness, recommendation intentions, and offer acceptance intentions. In a more recent study, Schinkel et al. (2016) found that distributive justice perceptions were positively related to organizational attractiveness and recommendation intentions. Accordingly, the following is hypothesized:

Hypothesis 3: There will be a positive relationship between perceptions of distributive justice and a) attraction to the organization, b) job acceptance intentions, and c) recommendation intentions.

Hypothesis 4: There will be a negative relationship between perceptions of distributive justice and litigation intentions.

The process described above, namely a relationship between selection decision and perceived distributive justice with distributive justice perceptions predicting applicant reaction outcomes, suggests that there might be a mediation effect such that favorability of the outcome influences applicant reactions through distributive justice perceptions. In order to examine this possibility, the following research question is proposed:

Research Question 4: Is there a mediation between AI use and applicant reactions through distributive justice perceptions?

In addition to their main direct and indirect effects on justice perceptions and applicant reactions, it is likely that the use of AI and outcome favorability will interact in predicting procedural and distributive justice perceptions. Such an interaction effect was proposed by Gilliland (1993) who suggested that procedural rules (e.g., job relatedness, selection information) would have the greatest impact on fairness perceptions when distributive rules have been violated whereas distributive rules would have the greatest impact on fairness perceptions when procedural rules are violated. In fact, there is evidence indicating that an interaction between AI use and outcome favorability in predicting justice perceptions might exist. For example, Schinkel, van Vianen, and van Dierendonck (2013) found that higher perceptions of procedural justice were associated with higher organizational attractiveness for rejected applicants but not for accepted applicants. These authors also found that selection outcome had the strongest effect on organizational attractiveness when procedures were perceived to be unfair. In addition, Brockner and Wiesenfeld (1996) found that procedural and distributive justice perceptions interactively combined in explaining individuals' reactions to organizations such that procedural fairness was more positively related to reactions when outcome favorability was low.

Indeed, there appears to be a self-serving effect in this seemingly complex relationship such that when the outcome is unfavorable, individuals engage in self-enhancing attributions and attribute the outcome to the process rather than their own performance (Ababneh, Hackett, & Schat, 2014; Chan, Schmitt, Jennings, Clause, & Delbridge, 1998; Ployhart & Harold, 2004; Ryan & Ployhart, 2000; Schinkel et al., 2016). In the context of the current study, this would indicate that those who are rejected would have low levels of procedural justice perceptions regardless of the medium used, whereas those who are accepted would be more likely to be influenced by procedural justice rules as defined by Gilliland (1993). Accordingly, we expect that AI use and outcome favorability will combine in predicting perceptions of procedural and distributive justice and hypothesize the following:

Hypothesis 5: Outcome favorability will moderate the relationship between AI use and a) perceived procedural justice and b) perceived distributive justice such that the relationship will be stronger for accepted applicants.

Finally, it is possible that experience and familiarity with computers may moderate the effect of the use of AI on applicant reactions (Anderson, 2003; Bauer, Truxillo, Tucker, Weathers, Bertolino, Erdogan, & Campion, 2006; Wiechmann & Ryan, 2003). Gilliland (1993) listed applicants' prior experience as a moderator of the relationship between antecedents of procedural and distributive justice and perceptions of process fairness, and proposed that prior experience with a selection system would affect fairness perceptions regarding that procedure. It is likely that for applicants who are less familiar with computers and thus have low levels of self-efficacy, the relationship between the use of AI and procedural and distributive justice perceptions will be stronger since the system would likely be seen as a highly novel situation (Bauer et al., 2006). However, for those with high-levels of self-efficacy with computers, the use of AI may not have a significant effect on fairness perceptions. In support of this argument, Wiechmann and Ryan (2003) found that experience with computers influenced perceptions of the selection process such that both basic and technical computer experience were positively related with perceptions of process fairness. This suggests that applicants' reactions to the use of AI will be moderated by their self-efficacy with computers. Accordingly, the following is hypothesized:

Hypothesis 6: Self-efficacy with computers will moderate the relationship between the use of AI and perceptions of a) procedural justice and b) distributive justice such that the relationship will be stronger for those with low levels of self-efficacy.

Method

Participants and Procedure

MTurk workers who participated in an online survey (*N* = 320) were randomly presented one of four vignettes, each describing a selection scenario in which the decision-maker (human vs. AI) and the outcome (accept vs. reject) were manipulated, leading to a 2x2 experimental design. Specifically, the vignettes asked the participants to imagine they were applying for a position in which they were seriously interested, and described the process after job application with either human interaction (e.g., HR manager reviews the resume and then interviews face-to-face) or AI interaction (e.g., resume screening by a software, which is followed by a digital interview scored by an algorithm). Each situation ended with either a job offer or a rejection decision, leading to four vignettes (see Appendix-A). After reviewing one of the vignettes, participants responded to items measuring their justice perceptions, organizational attraction, job pursuit intentions, recommendation intentions, litigation intentions, and self-efficacy with computers. Two attention check items were also included in the surveys, and participants who failed either item were not included in the analyses, resulting in a final sample size of $N = 298$. Participants were 56% male and 42.3% female (2 participants did not answer), and the mean age was 38.71 ($SD = 11.09$).

Measures

Procedural justice. Perceptions of procedural justice were measured by using six Likert-type items (1-strongly disagree to 5-strongly agree) adapted to the current study from the Selection Procedural Justice Scale developed by Bauer, Truxillo, Sanchez, Ferrara, and Campion (2001). Specifically, job relatedness and chance to perform dimensions of the scale were used to measure procedural justice in the current study. A sample item was “Doing well during this hiring process means a person can do a job well”. The internal consistency reliability of the scale was .94 in the current study.

Distributive justice. Perceptions of distributive justice were measured using three Likert-type items (1-strongly disagree to 5-strongly agree) from Organizational Justice Measure developed by Farago, Zide, and Shahani-Denning (2013). Items were adapted to the context of the current study. A sample item was “The selection decision was probably justified, given this hiring process”. The internal consistency reliability of the scale was .92 in the current study.

Organizational Attraction. Attraction to the organization was measured using four Likert-type general attractiveness items (1-strongly disagree to 5-strongly agree) from the Organizational Attraction Scale developed by Highhouse, Lievens, and Sinar (2003). A sample item was “For me, this company would be a great place to work”. Internal consistency reliability of the scale was .95 in the current study.

Job pursuit intentions. Intentions to pursue employment were measured by using three Likert-type items (1-strongly disagree to 5-strongly agree) from the intentions to pursue sub-scale of Organizational Attraction Scale developed by Highhouse et al. (2003). A sample item was “I would accept a job offer from this company”. Internal consistency reliability of the scale was .87 in the current study.

Recommendation intentions. Intentions to recommend the organization were measured by using one Likert-type item (1-strongly disagree to 5-strongly agree) from the intentions to pursue sub-scale of Organizational Attraction Scale developed by Highhouse et al. (2003). The item was “I would recommend this company to a friend looking for a job”.

Litigation intentions. Intentions to litigate were measured by using four Likert-type items (1-strongly disagree to 5-strongly agree) developed by Stoughton, Thompson, and Meade (2015). A sample item was “An organization that uses a hiring system like this would likely be sued by applicants”. Internal consistency reliability of the scale was .95 in the current study.

Self-efficacy with computers. Computer self-efficacy was measured using five Likert-type items (1-strongly disagree to 5-strongly agree) in the first factor of Subjective Computer Experience Measure developed by Yaghmaie (2007). A sample item was “I feel confident about using computers”. Internal consistency reliability of the scale was .83 in the current study.

Results

The measurement model of the study variables was tested through confirmatory factor analytic methods by using MPlus 7.0 software. Maximum likelihood estimator was used to estimate factor loadings. First, we tested a model in which all observed variables loaded onto their hypothesized latent factors. The results of the model showed a high level of fit with the data, χ^2 (260, N = 298) = 592.31, p < .001, CFI = .95, TLI = .95, RMSEA = .07. In order to test for the possibility of common method bias, an alternative model was tested in which all the observed variables loaded onto a single factor. The resulting model demonstrated very poor fit with the data, χ^2 (275, N = 298) = 3981.62, p < .001, CFI = .47, TLI = .43, RMSEA = .21, providing evidence that common method variance was not present. Finally, we tested an alternative model in which all procedural and distributive justice items loaded on one factor and organizational attraction, recommendation intentions, and job pursuit intentions items loaded on a general attraction factor. This model also resulted in inadequate fit with the data, χ^2 (293, N = 298) = 1202.2, p < .001, CFI = .88, TLI = .86, RMSEA = .10, suggesting that participants were able to distinguish between different indicators of justice perceptions and organizational attraction. The means and standard deviations of and correlations between the variables used in the study are presented at Table 1.

The first research question asked if perceptions of procedural justice would be influenced by the use of AI in selection decisions. The results of an independent samples t-test analysis indicated that procedural justice perceptions were significantly lower for the AI group (M = 2.75, SD = 1.07) than the face-to-face group (M = 3.19, SD = .97), t(296) = 3.68, p < .001. Next, the relationship between perceived procedural justice and applicant reaction outcomes (Hypotheses 1a, 1b, 1c, and 2) was examined using Pearson correlations. As seen in Table-1, all the correlations were significant and in the expected directions, supporting the hypotheses. Finally, we tested the path from AI use to applicant reaction outcomes through perceived procedural justice (RQ-2) using a path model analysis on MPlus (see Table-2). An examination of Table-2 reveals that all the direct and indirect effects are significant between AI use and organizational attraction, job pursuit intentions, recommendation intentions, and litigation intentions, indicating that a partial mediation exists between AI use and these variables through procedural justice perceptions.

Research Question 3 asked if perceptions of distributive justice would be influenced by the use of AI in selection decisions. The results of an independent samples t-test analysis indicated that distributive justice perceptions were significantly lower for the AI group (M = 3.08, SD = 1.06) than the face-to-face group (M = 3.42, SD = 1.04), $t(296) = 2.80$, $p < .01$. Next, the relationship between perceived distributive justice and applicant reaction outcomes (Hypotheses 3a, 3b, 3c, and 4) was examined using Pearson correlations. As seen in Table-1, all the correlations were significant and in the expected directions, supporting the hypotheses. Finally, we tested the path from AI use to applicant reaction outcomes through perceived distributive justice (RQ-4) using a path model analysis on MPlus (see Table-2). An examination of Table-2 reveals that all the indirect effects were significant, suggesting the presence of a partial mediation between AI use and applicant reaction outcomes through perceived distributive justice.

In addition to examining the mediation effects separately for procedural and distributive justice perceptions, we tested the combined effects for each applicant reaction outcome variable to examine the relative importance of procedural and distributive justice as mediators between AI use and applicant reactions (see Table-2). An examination of the table reveals that the larger part of the indirect effect from AI use to organizational attraction, job pursuit intentions, and recommendation intentions is through procedural justice perceptions. However, for litigation intentions, both variables seem to carry equal weight in the process, and most of the effect from AI use is direct. Finally, we tested the full mediation model in which AI use predicts procedural and distributive justice perceptions which predict applicant reaction outcomes. This model had very good fit with the data, χ^2 (191, N = 298) = 523.07, p < .001, CFI = .95, TLI = .94, RMSEA = .08.

Hypothesis 5a suggested that outcome favorability would moderate the relationship between AI use and perceived procedural justice such that it would be stronger for accepted applicants. A two-way ANOVA in which AI use and outcome favorability (i.e., accept vs. reject) were independent variables and perceived procedural justice was the dependent variable yielded a main effect for AI use, $F(3, 294) = 15.46$, $p < .001$, such that procedural justice was significantly lower in the AI condition (M = 2.75, SD = 1.07) compared to the face-to-face condition (M = 3.19, SD = .97). The main effect for outcome favorability was also significant, $F(3, 294) = 12.42$, $p < .001$, with those who were rejected having significantly lower procedural justice perceptions (M = 2.78, SD = .97) than those who were accepted (M = 3.16, SD = 1.08). Finally, the interaction term was also significant, $F(3, 294) = 4.74$, $p < .05$, indicating that the effect of AI was stronger for those who are accepted compared to those who are rejected. Thus, Hypotheses 5a was supported (see Figure-2). Hypothesis 5b suggested that outcome favorability would moderate the relationship between AI use and perceived distributive justice such that it would be stronger for accepted applicants. A two-way ANOVA in which AI use and outcome favorability (i.e., accept vs. reject) were independent variables and perceived distributive justice was the dependent variable yielded a main effect for AI use, $F(3, 294) = 8.54$, $p < .01$, such that distributive justice was significantly lower in the AI condition (M = 3.08, SD = 1.06) compared to the face-to-face condition (M = 3.42, SD = 1.04). The main effect for outcome favorability was also significant, $F(3, 294) = 4.78$, $p < .05$, with those who were rejected having significantly lower distributive justice perceptions (M = 3.13, SD = 1.00) than those who were accepted (M = 3.38, SD = 1.11). However, the interaction term was non-significant, $F(3, 294) = .98$, $p = .322$, indicating that the effect of AI on distributive justice perceptions does not change based on outcome favorability. Thus, Hypotheses 5b was not supported.

Finally, Hypothesis 6 proposed that the relationship between a) procedural and b) distributive justice perceptions would be moderated by computer self-efficacy. Results of the regression analysis in which self-efficacy variable was centered and entered into the equation with AI use in the first step and the interaction term was added in the second step indicated that the interaction term was non-significant in predicting procedural justice perceptions, $b = -.09$, $p = .705$, leading us to reject Hypothesis 6a. Hypothesis 6b also did not receive support with the interaction term failing to reach significance, $b = -.01$, $p = .978$, indicating that self-efficacy with computers does not influence the relationship between AI use and justice perceptions.

Discussion

With new technologies such as the use of AI in staffing being endorsed by organizations at a pace much beyond that of research, it is important that these new methods be subjected to research scrutiny. In addition to pressing concerns such as their validity and legality, one important aspect of the needed research is whether applicants view these practices positively. Accordingly, given the importance of applicant reactions to staffing procedures in influencing a number of important organizational outcomes (McCarthy et al., 2017), this study examined applicants' reactions to the use of AI in staffing by organizations. To that end, we utilized an experimental approach in which participants viewed vignettes describing a hiring situation in which either a digital interview through AI or a face-to-face interview by an HR manager is described. The favorability of the outcome is also manipulated such that in both conditions, the outcome was either a rejection or a job offer. The findings indicated that participants had significantly less favorable reactions in the AI condition compared to the face-to-face condition in terms of attraction to the organization, intentions to pursue a job, intentions to recommend the organization to others, and intentions to seek legal action. While this effect was partially mediated through perceived procedural and distributive justice, a large portion of the effect was direct from AI use to the reaction outcomes. Additionally, whether outcome favorability and computer self-efficacy influenced the effect of AI on applicant reactions was examined. While no interaction effect was observed for computer self-efficacy, there was a significant moderation in predicting perceived procedural justice such that the effect was stronger for those who were accepted.

This study has important theoretical and practical implications. First, the findings advance theory on applicant reactions and add to the accumulating evidence suggesting that applicants have more favorable reactions when they are provided with the opportunity to personally and physically interact with organizational agents instead of having to communicate through non-personal means (e.g., Chapman et al., 2003; Langer et al., 2017). Second, the study fills an important gap in the literature by addressing the calls to examine applicant reactions to decision-making by AI in the staffing process (Langer et al., 2017). The finding that even a sample of MTurk workers who arguably have high levels of familiarity with computers had negative reactions to the use of AI in selection is potentially troubling and may have important implications for organizations seeking to use AI in their selection processes. The results of this study suggest that organizations may consider embedding a certain amount of human interaction within their AI-based staffing systems at early stages in order to create the impression that the applicants are valued as individuals rather than data points feeding their machine learning algorithms. One way to achieve this can be combining the characteristics of digital interviews with that of video-conference interviews such that the interview is performed by HR personnel through video chat software while the responses are still recorded and processed by the machine learning algorithm. Organizations may also utilize brief phone conversations between the HR personnel and candidates before they go through digital interviews in which they are provided with information regarding the process and their questions are answered. Regardless of how it is achieved, the results of the current study suggest that it would be beneficial to maintain some level of human contact within the process.

One unexpected finding was that computer self-efficacy did not moderate the relationship between AI use and procedural and distributive justice perceptions. One possible explanation for this finding may be that the sample utilized in the current study, MTurk workers who arguably spend most their times completing tasks on a computer, had generally high levels of computer literacy and this created a restriction of range, resulting in this variable not having a significant influence on the relationship. In fact, examining the mean and variance statistics of the variable (see Table-1), it can be seen that the mean level was very high (4.6/5) while the variance was low. This indicates that most participants had similarly high levels of computer self-efficacy, potentially suppressing the effect this variable might have had if a more diverse sample was utilized. More research is needed utilizing samples with varying levels of computer literacy to investigate this issue.

One interesting finding was that while a significant portion of the effect AI use had on applicant reactions was moderated by justice perceptions, supporting a fairness-based approach to applicant reactions as proposed by Gilliland (1993), there was also a large direct effect of AI use on applicant reactions not accounted by the mediator variables examined in the current study. This suggests that the antecedents of unfavorable reactions to AI use cannot be reduced to fairness perceptions only. One potentially fruitful avenue for future research is applying an attribution-based framework to examine the mechanisms through which AI use influences applicant reactions. Ployhart and Harold (2004) proposed the Applicant-Attribution Reaction Theory (AART), which posits that applicant reactions are essentially driven by attributional processes in terms of locus (internal vs. external), controllability (controllable vs. uncontrollable), and stability (stable vs. unstable) and that fairness perceptions are consequences of this attributional processes and actually carry little explanatory power . The theory further proposes that to the extent that a selection decision is attributed to internal, stable, and controllable causes, favorable reactions should occur. In the context of reactions to AI use, this suggests that to the extent that individuals view decisions by machine learning algorithms as internal, stable, and controllable, they should develop positive reactions whereas the opposite should be true when AI is perceived to be external, unstable, and uncontrollable. Future research examining this possibility would be beneficial.

Finally, a moderation by outcome favorability was observed such that for the participants in the reject condition, perceptions of procedural justice were low in both the AI and face-to-face conditions, but for those who were in the accept condition AI use was associated with much lower perceptions of procedural fairness. This indicates that perhaps the group that is the most likely to have negative reactions when AI is used in staffing is the one that organizations arguably care most about: individuals who are being offered a job. The results suggest that lower perceptions of procedural justice associated with AI use may frustrate these applicants, leading them to potentially reject a job offer and therefore leading to recruiting time and resources being wasted, potentially nullifying the advantages organizations seek to gain from AI use in the first place.

As with any study, there are limitations with the current study that need to be addressed. The first limitation has to do with the sample utilized in the study. We tested the hypotheses on a sample of MTurk workers who are likely different from the general population in terms of their experience with computers. However, given we observed significantly less favorable reactions to AI use in such a sample, we believe the results would not change if we had utilized a sample more representative of the general population. In addition, we utilized an experimental design, which may lack the fidelity of an actual job application situation. Accordingly, in order to increase the generalizability of the findings, future research should attempt to investigate the issue in a field study, utilizing applicants to an actual job. However, despite the limitations regarding the sample and the methodology, this study fills an important gap in the literature and provides the first evidence that AI use by organizations is likely to be viewed unfavorably by potential employees.

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Table 1

Means, Standard Deviations, and Correlations among the Study Variables

	1	2	3	4	5	6	7	8	9
1. Procedural Justice	**.94**								
2. Distributive Justice	.45***	**.92**							
3. Organizational Attraction	.66***	.41***	**.95**						
4. Job Pursuit Intentions	.57***	.40***	.86***	**.87**					
5. Recommendation Intentions	.61***	.42***	.81***	.76***	**---**				
6. Litigation Intentions	-.23***	-.30***	-.42***	-.40***	-.39***	**.95**			
7. Computer Self-Efficacy	.02	.12*	.10	.17**	.05	-.19**	**.83**		
8. AI vs. Face-to-Face	-.21***	-.16**	-.29***	-.28***	-.26***	.40***	.01	**---**	
9. Accept vs. Reject	.18**	.12*	.25***	.20***	.23***	-.12*	.03	.06	---
Mean	2.97	3.26	3.22	3.46	3.22	2.23	4.60	.50	.51
SD	1.05	1.06	1.08	.99	1.07	1.13	.52	.50	.50

Notes. AI vs. Face-to-Face was coded as 0 = Face-to-face and 1 = AI. Accept vs. Reject was coded as 0 = Reject and 1 = Accept. * p < .05, ** p < .01, *** p < .001. Values on the diagonal are internal consistency reliabilities.

Table 2

Direct and Indirect Effects from AI use to Applicant Reaction Outcomes

Mediator		Organizational Attraction			Job Pursuit Intentions			Recommendation Intentions			Litigation Intentions		
		b	95% CI		*b*	95% CI		*b*	95% CI		*b*	95% CI	
			Lower	Upper		Lower	Upper		Lower	Upper		Lower	Upper
Procedural Justice	Total	-.30	-.41	-.19	-.28	-.40	-.17	-.26	-.37	-.15	.43	.33	.52
	Direct	-.17	-.26	-.08	-.17	-.27	-.07	-.14	-.23	-.05	.39	.29	.49
	Indirect	-.13	-.20	-.06	-.11	-.18	-.05	-.12	-.23	-.05	.04	.01	.07
Distributive Justice	Total	-.30	-.41	-.19	-.27	-.39	-.16	-.26	-.37	-.15	.43	.33	.52
	Direct	-.24	-.34	-.13	-.22	-.32	-.11	-.19	-.30	-.09	.37	.29	.48
	Indirect	-.06	-.11	-.02	-.06	-.11	-.01	-.07	-.11	-.02	.04	.01	.08
Combined	Total	-.31	-.42	-.21	-.29	-.41	-.18	-.27	-.38	-.17	.43	.34	.53
	Direct	-.16	-.25	-.07	-.16	-.27	-.06	-.13	-.22	-.04	.38	.28	.48
	Ind_P_Just	-.12	-.20	-.06	-.10	-.16	-.05	-.11	-.17	-.05	.02	-.01	.04
	Ind_D_Just	-.03	-.05	-.00	-.03	-.06	-.00	-.03	-.06	-.00	.04	.01	.07

Notes. AI vs. Face-to-Face was coded as 0 = Face-to-face and 1 = AI. Accept vs. Reject was coded as 0 = Reject and 1 = Accept.

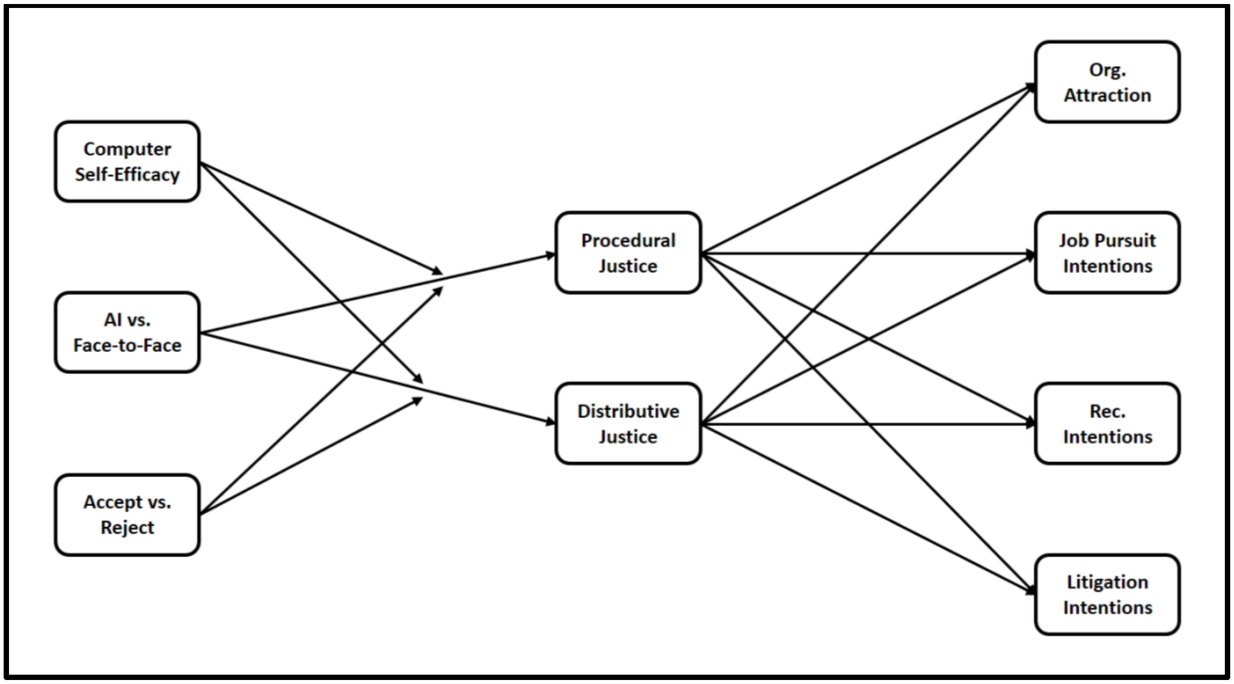

Figure 1. The proposed model.

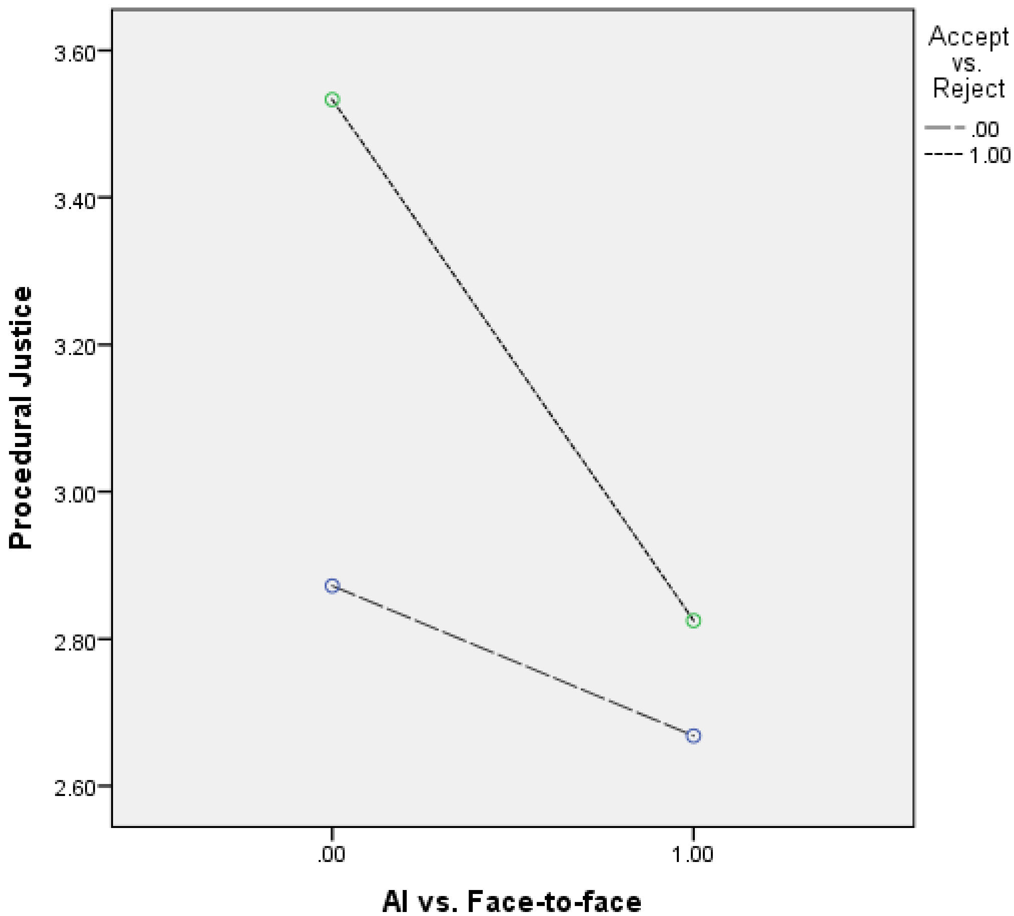

Figure 2. The interaction between AI use and outcome favorability in predicting perceived procedural justice. AI vs. Face-to-Face was coded as 0 = Face-to-face and 1 = AI. Accept vs. Reject was coded as 0 = Reject and 1 = Accept.

APPENDIX-A

FACE-TO-FACE CONDITION

Imagine you're applying for a position in which you're seriously interested. You're asked to submit your resume to the HR Manager. The HR manager reviews your resume and decides you're qualified for the next step of the selection process. They then ask you to have a face-to-face interview with your potential supervisor. During the face-to-face interview, the supervisor asks you five structured interview questions, such as "tell me about a time where you had to improve a process and how that has helped you in your career." After the interview, the supervisor stands up, shakes your hand, and thanks you for coming, saying they will let you know in two weeks the decision that they've made. Two weeks later, they call you and tell you they have decided to offer you the position (ACCEPT) / not to offer you the position (REJECT).

AI CONDITION

Imagine you're applying for a position in which you're seriously interested. You're asked to upload your resume on the company's website. The website informs you that your resume will be screened using an artificial intelligence software. This software evaluates your qualifications for the position using an advanced algorithm and decides to continue with the interview process. Next, you're sent a link via email to start the interview process using a webcam on your computer. Throughout the interview, the artificial intelligence software asks you structured interview questions, such as "tell me about a time where you had to improve a process and how that has helped you in your career." Your responses are recorded on the computer and then rated by the artificial intelligence software based on your vocal tone, recognition of facial expressions, and response content. The artificial intelligence software then makes a recommendation to the hiring manager. Two weeks later, they call you and tell you they have decided to offer you the position (ACCEPT) / not to offer you the position (REJECT).