ABSTRACT

Title of Thesis:	APPLICANT REACTIONS TO ARTIFICIAL INTELLIGENCE SELECTION SYSTEMS
	Rewina Bedemariam, Master of Arts, 2022
Thesis Directed By:	Professor Jennifer Wessel, Social, Organizational and Decision Sciences

Practitioners have embraced the use of AI and Machine Learning systems for employee recruitment and selection. However, studies examining applicant reactions to such systems are lacking in the literature. Specifically, little is known about how job applicants react to AI-based selection systems. This study assessed fairness perceptions of hiring decisions made by AI-driven systems and whether significant differences existed between different groups of people. To do so, a two-by-two experimental study where participants in a selection scenario are randomly assigned to a decision-maker condition (human vs AI) and outcome variability condition (hired vs rejected) was utilized. The results showed that the condition had a significant effect on the interactional justice dimension. The interaction effect of outcome and condition had an impact on job relatedness, chance to perform, reconsideration opportunity, feedback perceptions, and interactional justice. The three-way interaction of outcome, race and condition influences general fairness reactions and emotional reactions. Given these findings, HR personnel should weigh the pros and cons of AI, especially towards applicants that are rejected.

APPLICANT REACTIONS TO ARTIFICIAL INTELLIGENCE SELECTION SYSTEMS

by

Rewina Bedemariam

Thesis submitted to the Faculty of the Graduate School of the
University of Maryland, College Park, in partial fulfillment
of the requirements for the degree of
Master of Arts
2022

Advisory Committee:
Professor Jennifer Wessel- Chair
Professor James Grand
Professor Linda Zou

Table of Contents

List of Tables

List of Figures

List of Abbreviations

AI: Artificial Intelligence

ML: Machine Learning

AR: Applicant Reactions Theory

I/O: Industrial/Organizational Psychology

SIOP: Society for Industrial and Organizational Psychology

RBIM: Race Based Identity Management

SBIM: Social Based Identity Management

Chapter 1: Introduction

The recruitment and selection process has undergone several changes as the information technology realm has evolved. In the initial stages of the IT transformation, multimedia, and the Internet were leveraged to digitize some of the labor-intensive aspects of recruitment (Gardner, Lepak, & Bartol, 2003). Career portals, job boards, and social networking sites have enabled this transition (Marler & Fisher, 2013; Ensher, Nielson, & Grant-Vallone, 2002). There has been a marked growth in the use of technology in the recruitment and selection process, with 74% of large U.S. organizations using some form of electronic selection tools to help with the hiring process (Stone, Deadrick, Lukaszewski, & Johnson, 2015). New advances in technology have brought changes to how HR automates many of its functions including performance management, online surveys, employment applications, onboarding, and so forth (EEOC, 2016; Johnson & Verdicchio, 2017).

The latest of these technological mediums used in recruitment and selection include asynchronous video interviews, game-based assessments, and other similar selection systems based on Machine Learning (Behrend, & Landers, 2019; EEOC, 2016). Organizations are now leveraging the use of Artificial Intelligence (AI) and Machine Learning (ML) to partially or fully automate selection decisions (EEOC, 2016; Stephan, Brown, & Erickson, 2017). Due to this boom in technology-mediated employee applications systems, more individuals have had their resumes and video interviews evaluated by AI-powered selection tools that capture applicants' information (Behrend, & Landers, 2019; Handler & Hunt, 2003). The use of AI/ML tools within the talent acquisition arena has been on the rise with an estimated 33% of

organizations adopting such tools for speedy and efficient recruitment and selection purposes (Stephan, Brown, & Erickson, 2017). Numerous technology vendors and companies offer various AI/ML-based applications, such as those that score asynchronous video interviews (e.g., HireVue, Montage), some others that use game-based job assessments (e.g., Pymetrics, Knack), and even others that scrape social media profiles to assess person-job fit (e.g., Entelo).

These AI-based tools could offer numerous benefits in the job application and hiring decision-making process. They result in more efficient decision making and standardized selection processes. The algorithms themselves can also be adjusted as more data is collected, resulting in increased accuracy over time (e.g., EEOC, 2016; Johnson & Verdicchio, 2017).

Doubts, however, arise at the inner workings of the algorithm itself (often) termed "black box"). These include the use of datasets that lack information or disproportionately represent certain populations, as well as the application of poorly designed models that lack sound theoretical and scientific ground (Basch & Melchers, 2019). They might maintain or even amplify systematic discrimination perpetuated by humans since such systems will "learn" to replicate human biases embedded in the datasets used (Caliskan, Bryson, & Narayanan, 2017; O'Neil, 2016). In fact, studies and new reports have emerged showing AI enabling and aggravating bias, including news reports of biases of AI in facial recognition systems (HBR, 2019).

Moreover, there is an apparent lack of public scientific evidence or research regarding the reliability, validity, and fairness of these tools, motivating the need for

the professional involvement of Industrial/Organizational (I/O) psychologists. Although the goal of AI tools is to increase the accuracy and efficiency of the hiring process, the perceptions and attitudes that people have of them are critical aspects that should be explored (Lee, 2018). Perceptions of fairness of selection procedures impact perceptions of the organization, recommendation intentions, and job acceptance intentions (Hausknecht, Day & Thomas, 2004). Fairness perceptions have been found to have a moderate positive relationship with organizational attractiveness (Hausknecht et al., 2004; Bauer et al., 1998). Therefore, asking how applicants perceive and react to being evaluated by Artificial Intelligence tools, particularly when they are evaluated negatively, is important and is the subject of this study. This study further poses the questions of how individuals from minority groups who have had prior experiences of discrimination react to being evaluated by these tools.

While several authors have studied justice perceptions and general applicant reactions toward internet-based selection procedures (Bauer, Truxillo, Tucker, Weathers, Bertolino, Erdogan, & Campion, 2006), asynchronous video interviews (Brenner, Ortner, & Fay, 2016), and improving applicant reactions towards asynchronous video interviews (Basch, & Melchers, 2019); the use of new technology such as AI and applicants' reactions to them is highly understudied (Marler & Fisher, 2013; Bondarouk & Brewster, 2016). To close this gap, I/O psychologists are attempting to be a part of the design and evaluation of such systems as there have been calls for more studies of these selection systems (SIOP, 2019). This study sought to answer some of these calls and bridge gaps in the literature by exploring applicant reactions to recruitment and selection decisions made by AI.

Specifically, there was an attempt to answer calls from researchers to include other variables of interest such as the use of technology and person-based characteristics to the applicant reactions literature (see Ryan & Ployhart, 2000).

Person-based characteristics (race) was also explored to see if there are group differences in how such AI-based selection systems are perceived in terms of fairness. To do so, race-based impression management theory (RBIM), which posits that minorities utilize specific strategies aimed at increasing chances for a positive outcome based upon one's membership in a racial identity group was used (Morgan, 2002; Roberts, 2005; Roberts et al., 2008, Roberts et al. 2014). Specifically, the hypotheses were built through the lenses of these two theories- applicant reactions theory (ART) and race-based identity management (RBIM).

Significance and Aims

The study is significant to the field for several reasons:

First, there was an attempt to extend the applicant reactions literature to examine applicant reactions to AI evaluations. Gilliland's model of Applicant Reactions Theory (1993) brought to focus those perceptions of fairness are products of interactions between applicants and the hiring organizations. The theory also outlines several situational and personal factors that affect applicants' perceptions of fairness. Despite the numerous studies based on this theory (e.g., Bauer et al., 2001; Hausknecht et al., 2004; Truxillo et al., 2009); Ryan & Ployhart, 2000; Ployhart & Ryan, 1998), very little is out there that examines the role of technology, especially AI-based selection systems as a situational factor that could affect applicant reactions.

Understanding fairness reactions to AI decision-makers is important given the exponential rise in the use of technologies in the HRM context (Stephan et al, 2017; Stone et al., 2015; Anderson, 2003). Currently, many people lack familiarity with how AI/ML works (Johnson & Verdicchio, 2017), which makes AI/ML-based systems appear cryptic, opaque, and less fair to applicants. This study helps expand our understanding of the effects of AI on justice perceptions.

In addition to a lack of AI-based technology as a situational factor in AR theory, very few studies have explored individual differences/person characteristics in the theory as well. This is despite calls from researchers to include individual differences in applicant reactions research (Ryan & Polyhart, 2000). Therefore, in addition to the exploration of AI technology in AR-theory, individual differences in race as potential personal factors that affect perceptions of fairness in the selection process. This is because minorities have experiences that can influence their perceptions of fairness such as past experiences of prejudice, discrimination, and stereotyping. To cope with these experiences of discrimination, many might employ impression management strategies to have a greater sense of control over their outcomes such as acceptance in a job application (Neel et al., 2013; Shih et al., 2013; Gioaba, & Krings, 2017). However, in AI-based selection systems, applicants may perceive less control over their outcomes because there may be fewer opportunities to appeal decisions, express opinions, or manage impressions (Gonzalez et al., 2019). This lack of opportunity for impression management may be perceived as less fair for those who have experiences of discrimination and prejudice based on their minority status and race. Race-based Identity Management theory (RBIM) which is based on

Social Identity theory (Roberts, 2005; Tajfel & Turner, 1979), asserts that those with socially devalued or stigmatized identities employ certain ways of impression management to be viewed more favorably. This theory was used to guide the exploration of fairness perceptions and group differences to AI evaluations. This study could also expand on race-based impression management theory which has been used to explore the work lives of racial minorities once they are in the workforce (Morgan, 2002; Roberts, 2005; Roberts, Settles & Jellison 2008). In this current research, the author is extending the racial impression management theory by incorporating racial minority individuals' reactions to AI and what an AI-based automated system would mean for racial minorities who are applying for a job (application phase vs already in the workforce). Therefore, this study attempted to extend applicant reactions literature by integrating two overlooked but important factors: technology (AI) and group differences (race).

Third, determining how applicants react to the use of technology in the selection process serves to help organizations better understand how these practices affect job seekers' perceptions of the organization and establish a relationship between applicant reactions and applicant behavioral outcomes (Bauer, Truxillo, Paronto, Weekley, & Campion, 2004; Highhouse, Lievens, & Sinar, 2003; Truxillo & Bauer, 2011). Negative applicant reactions lead to outcomes such as withdrawal from the selection process, which dampens the utility of the selection system and potentially curbs potential employees from joining the company (Ryan, Sacco, McFarland & Kriska, 2000). The organization could also seem unattractive to top candidates, decrease acceptance intentions, and may increase intentions to litigate

(Geenen, Proost, Dijke, Witte, Grumbkow, 2012). Candidates with negative reactions to a company's selection system may also dissuade other potential employees from applying to the company (Hausknecht, Day & Thomas, 2004). Since managing a positive image is important for an organization during the selection process, the findings can assist HR managers in weighing the advantages and disadvantages of using computer-mediated selection systems versus traditional selection procedures. In addition, the exploration of potential differences in applicant reaction in terms of minority status could bring to the forefront issues that are relevant for companies and society. Were there to be significant differences among different groups, this study aimed to highlight the problems and challenges of AI-powered applicant systems.

Finally, the study also attempted to address the Society of Industrial-Organizational Psychology (SIOP) call for research on new technology powered selection systems and calls from IO psychologists to advance this topic (Behrend & Landers, 2019; Gonzalez, Capman, Oswald, Theys, & Tomczak, 2019). It is clear that the design and implementation rates of AI/ML applications are outpacing relevant scientific research and legal guidelines. The proprietary nature of such systems coupled with their potential for biases warrants a timely investigation on the many aspects of these technologies, including the perceptions of applicants who are evaluated through them. We as researchers have limited access to these proprietary AI tools that are utilized by these companies despite the potential limits of the technologies and the ethical questions that remain unanswered. This makes it difficult to produce publications in this new and emerging area of selection and recruitment

broadening the scientist-practitioner gap (Dastin, 2018). As such, this study sought to carry out a timely exploration of applicant reactions to AI-powered HR decisions.

Chapter 2: Literature Review

AI in Organizations

As noted above, some of the organizations that seek to attract and hire highly qualified applicants have turned their attention towards these systems and utilize AI and ML models to recruit and select candidates (Van Esch, Black, and Ferolie, 2019). An estimated 33% of organizations have adopted such tools for speedy and efficient recruitment and selection purposes (Stephan, Brown, & Erickson, 2017). Furthermore, there are numerous technology vendors and companies that offer various AI/ML-based job application systems such as HireVue, Montage, Pymetrics, Knack, and many others with different specializations like asynchronous videos, use of social media profiles and so on.

AI systems in human resources (HR) have been performing a variety of organizational tasks including personnel selection and evaluation with some degree of success (Chalfin et al., 2016; Kuncel, Klieger, Connelly, & Ones, 2013). For example, a study by Hoffman, Kahn, & Li (2018) demonstrated that their algorithms made hiring decisions that decreased the attrition rate of service sector employees. A study by Chalfin and colleagues (2016) showed how ML approaches were able to select police officers less likely to abuse citizens and teachers more likely to be effective (Chalfin et al., 2016). Organizations are developing their people analytics departments and numerous companies have started offering such services to other

companies to achieve similar successes (Campion, Campion, Campion, & Reider, 2016; Pennebaker & Graybeal, 2001). Businesses are capitalizing on this newfound ability by overhauling the ways in which they source and evaluate candidates.

These benefits of efficiency notwithstanding, their inner workings and the potential for bias raises questions. For example, doubts arise about the data used as input for an algorithm and the inner workings of the algorithm itself (often termed "black box"). These include data sets that lack information or disproportionately represent certain populations, as well as poorly designed models that lack sound theoretical and scientific ground. Algorithmic outputs are only as good as the instructions within the algorithm itself and the inputs used; an algorithm based on flawed assumptions or instructions will produce flawed conclusions (Basch, & Melchers, 2019). In fact, they might maintain or even amplify systematic discrimination perpetuated by humans since such systems will "learn" to replicate human biases embedded in the datasets used (Caliskan, Bryson, & Narayanan, 2017; Mann & O'Neil, 2016). For example, Amazon's hiring AI algorithm was scrapped because it was sexist. It was trained using the company's past data which is believed to be inherently flawed (Hong, Choi, & Williams, 2020).

As such, although AI makes several hopeful promises for a more efficient, effective, and enjoyable talent selection experience, many topics relevant to traditional testing deserve future research attention for AI tools such as their reliability, validity, fairness, transparency, acceptance by job seekers, and legality. Moreover, studies about how participants react to being evaluated by AI and justice perceptions also warrants to be studied.

While there are some studies that explore technology acceptance in the selection context broadly, such as asynchronous video interviewing (e.g., Brenner, Ortner, & Fay, 2016; Langer et al., 2017; Basch & Melchers, 2019), only one study has been done specifically on the reactions of applicants to being evaluated by AI systems for job applications. This study, which was conducted by Gonzalez et al., (2019), asked participants to imagine being evaluated for a job by an AI and another set of participants to imagine being evaluated for a job by human resources personnel. The study had three main findings. First, people generally react unfavorably toward AI and the organizations that use them for selection purposes. Secondly, these reactions appeared to have been due to concerns of interpersonal treatment (i.e., interactional justice, communication, privacy, trust), rather than procedural justice concerns. Thirdly, these fairness perceptions were coupled with emotional reactions such as "anger, skepticism, and reduced hope and excitement during the selection process" (p. 10).

Studies like these mentioned above responded to calls for more research on new technologies in personnel selection (Blacksmith, Willford & Behrend, 2016). However, these studies have methodological limitations. They were hypothetical vignette studies where participants had to imagine being evaluated by an AI. Therefore, questions remain about the effect of AI evaluations and if they hold for more realistic job applications. On top of these methodological inadequacies, there is still a dearth of timely research that centers on job applicants' reactions to hiring/rejection decisions made by AI systems as compared to human resources personnel and its acceptance among minority groups. In addition to a lack of more

thorough explorations of AI-powered application systems, there is also an expressed concern that practice outpaces publications, suggesting a lag between practice and research. As such, the proposed study aims to delve into this novel path and explore these new personnel selection technologies and gauge applicants' reactions to hiring decisions made by AI systems. In addition to that, it explored if there are differences in reactions and fairness perceptions to such technologies across racial groups which to the best of the researcher's knowledge has not been done.

In the following section, focus will turn to the organizational justice literature as a way of understanding how individuals might react to AI-mediated selection to that of human-made selection decisions. Applicant reaction theory, which emerged from Organizational justice theory will be elaborated upon below.

AI and Justice Perceptions

Born out of Adam's equity theory, Organizational justice has emerged as a popular conceptualization of fairness perceptions in work-related contexts (Greenberg & Cropanzano, 2001). It refers to the perceived fairness of organizational outcomes, procedures, and interpersonal treatment (Greenberg, 1987). It is comprised of the following four main dimensions:

Procedural justice is concerned with an individual's perceptions of the fairness of a particular process (Thibaut & Walker, 1975) rather than solely the outcome of that process. It emphasizes socio-emotional aspects in which a decision is rendered. This dimension emphasized the processes of the procedures during job application.

Interactional justice is the third component of organizational justice theory. Relationships supply economic and socio-emotional benefits (Cropanzano & Schminke, 2001). They signal "the present or future attainment of material or socioemotional benefit" whereas "injustice signals the absence of such valued beliefs" (Folger & Cropanzano, 2001, p. 27). Interactional justice has two aspects: interpersonal justice and informational justice. Interpersonal justice describes the perceptions of fairness related to interpersonal interactions between the individual and the person or entity that distributes a certain outcome. It underlies an individual's belief that persons or entities involved in rendering a decision/outcome treated them fairly. Informational justice, on the other hand, captures individuals' beliefs that they were provided with adequate amounts of information about processes and outcomes (how to get certain outcomes, etc).

Distributive justice is concerned with the fair distribution of particular outcomes of a process (Greenberg & Cropanzano, 2001). They are perceptions based on what an individual received as a result of a certain procedure. In this study, the outcome will be rejection or offer given by either the human decision-maker or by the AI decision-making system.

These above-mentioned justice components have been well researched including procedural justice (Bauer, Truxillo, Sanchez, Craig, Ferrara, & Campion, 2001), distributive justice (Pan, Chen, Hao, & Bi, 2018; Flint, & Haley, 2013; Smither et al., 1993), interpersonal justice (McNall, & Roch, 2007; Ryan & Chan, 1999), informational justice (Cheung, 2013; Bauer, Maertz, Dolen, & Campion, 1998). A meta-analysis by Hausknecht et al., (2004) demonstrated the unique

contribution of each type of the four types of justice explored above to commonly studied applicant reactions variables (e.g., job acceptance, recommending a friend). The next section will explore fairness perceptions in the application process and which fairness rules seem compromised either in AI-powered or human decision-maker job applications.

1) Applicant Reactions and Fairness Perceptions

Fairness rules and perceptions are an important part of applicant reactions to a hiring procedure, because applicants' perceptions of fairness directly influence subsequent attitudes and behaviors both during and after hiring (Konradt, Warszta, & Ellwart, 2013; Hausknecht, Day, & Thomas, 2004; Truxillo, Bauer, Campion, & Paronto, 2002). These fairness perceptions, also known as *applicant reactions, refer* to "attitudes, affect, or cognitions an individual might have about the hiring process" (Ryan & Ployhart, 2000, p. 566). Applicant reactions theory stems directly from Gilliland's (1993) studies which are concerned with the ability of organizations to elicit positive reactions from job applicants. A common way to measure these positive or negative reactions towards employee selection systems is to measure their perceptions of fairness.

As stated above, some studies have suggested that applicant reactions can be affected by novel technologies (e.g., Blacksmith, Willford, & Behrend, 2016). It is the hypothesis of this paper that AI-based hiring will affect how fairness is perceived. AI is likely to be seen as less fair because 1) it violates certain rules of procedural and interactional justice that are discussed below and 2) there is a lack of familiarity with

this type of technology among the laity. (Johnson & Verdicchio, 2017, Gonzalez et al., 2019). These procedural and interactional justice rules are discussed in the following section.

Procedural Justice

Procedural justice is the extent to which the process used to decide the outcomes of applicants is deemed fair. Gilliland's (1993) model proposes 10 procedural justice rules which include: *Job-relatedness* which refers to the "extent to which a test appears to measure content relevant to the job situation or appears to be valid" (Gilliland, 1993, p.703). It is what we commonly call face validity. Studies have shown that certain types of tests such as work samples are perceived positively in terms of job-relatedness than others like cognitive and personality tests (Hausknecht, Day, and Thomas, 2004). Bauer, Maertz, Dolen, and Campion (1998) found that job-relatedness of tests were positively related to applicants' perceptions of fairness. However, it surmised that this dimension would not have major differences among the two conditions because the questions posed are related to the job in both conditions.

Opportunity to perform refers to job applicants' ability to demonstrate their knowledge, skills, and abilities in a selection process (Gilliland, 1993). It is assumed to be related to the organizational justice concept of "voice" (Arvey & Sackett, 1993). Several studies have demonstrated that applicants' perceptions of the opportunity to perform in selection tests are related to positive perceptions of the process (Bertolino & Steiner, 2007; Nikolaou & Judge, 2007;

Schleicher, Venkataramani, Morgeson, & Campion, 2006). The researcher hypothesized this dimension would likely vary substantially with an AI compared to a human decision-maker. That is, there would be differences in the perception that applicants have as to which platform would allow for more of an opportunity to perform.

Reconsideration opportunity was described by Gilliland (1993) as an opportunity for a "second chance." Bauer et al. (2001) further defined and clarified it as "the opportunity to challenge or modify the decision making/evaluation process and the opportunity to review and/or discuss scores and scoring" (p.391). I surmised that there may be differences between the conditions for this dimension since people would perceive HR personnel as more reachable for a reconsideration opportunity. This may be perceived as lacking or difficult in the AI condition. Thus, it was hypothesized that differences may exist in fairness perception in this dimension between the conditions.

Feedback on the other hand denotes the information given to applicants about their performance. It emphasizes both timing at which the feedback is given and the content of that feedback (Gilliland, 1993). For this study, feedback is related to applicant reaction since the timeliness and content of the feedback given by a human rater versus a computer may elicit different reactions or be perceived differently. I hypothesized that we could see differences in this dimension between the conditions.

Each rule serves an important role in maintaining the fairness perception of an application process. There is not enough theoretical research to determine a priori

which dimension of procedural justice factors would be more salient to affect perceptions towards AI-based hiring (Garbers, 2016). However, we do know from past research that job-relatedness and opportunity to perform are especially important in determining positive reactions to selection processes (Bauer et al., 1998; Hausknecht et al., 2004; Schleicher, Venkataramani, Morgeson, & Campion, 2006). Out of the procedural justice dimensions, there are some factors that are more relevant to understanding reactions to human versus AI decision-makers than other factors. For example, *opportunity to perform,* which refers to one's ability to demonstrate their knowledge, skills, and abilities in a selection process would likely vary substantially with an AI compared to a human decision-maker. That is, there would be differences in the perception that applicants have as to which platform would allow for more of an opportunity to perform. Bauer et al. (2011) went to suggest that technological advances in selection and assessment may impact reactions towards the opportunity to perform dimension. For example, it is far easier to use impression management towards human resources personnel than AI. This has been found to be the case with other technology-mediated hiring mediums such as asynchronous videos (Bauer et al., 2004; Chapman et al., 2003). The explanation given as to why asynchronous videos illicit negative applicant reactions are the desire to engage in impression management and the perceived lack of opportunity to perform (Chapman, Uggerslev, & Webster, 2003; Straus, Miles, & Levesque, 2001). Moreover, other studies on technology such as computer-based testing, have also found that consistency, treatment of the applicants, and opportunity to perform were the strongest predictors of fairness perceptions (Dineen, Noe, & Wang, 2004;

Konradt, Warszta, & Ellwart, 2013). It is therefore conceivable that more advanced technology such as AI could also elicit more negative reactions than a human decision-maker. That is, AI decision-makers may lead applicants to question their ability to showcase their skills during the hiring process and consequently be doubtful as to whether they are able to control the situation. This study sought to assess both general reactions of justice perceptions and to also look at specific dimensions. However, it is believed by the author, that the rest of the factors will stay consistent/ uniform and will not serve as an appropriate basis for comparison purposes and were merely explored.

As such, the author hypothesizes:

H1: Applicants who receive selection decisions from an AI/ML procedure will have lower perceptions of opportunity to perform, feedback and reconsideration opportunity dimensions and overall lower general procedural justice perceptions than those applicants who received their decisions from human recruiters.

In a study by Gonzalez et. al, (2019), participants imagined that they were applying for a job that was rated either by a human decision-maker or an AI tool and to further imagine being either hired or rejected. Contrary to the hypothesis made in this study, their findings showed that procedural justice was not significantly varied between the conditions. This may be due to the nature of vignette studies where the participants were told to "imagine" applying for a job and "imagine" getting an evaluation from an AI or human decision-maker. Hence the adequacy and strength of the manipulation is questionable (Hall and Stevens, 1991). Hypothetical scenario

studies may not "fully capture the elements of reality under study" (Hughes & Huby, 2004, p.45). That is, there is a difference between what one "would ought to do" when imagining a scenario versus what one "would do" if they actually experienced it firsthand. This study investigated this relationship by examining the variables by using a methodology that has greater psychological fidelity.

Another potential reason for why procedural justice was not significantly different between the two conditions might be because the generalized procedural justice scale (SPJS) used by Gonzalez et al. does not capture where the differences in fairness lie. Instead, the researcher posits that using a longer version with all the subscales like opportunity to perform, reconsideration opportunity, job relatedness and so on, would show us where there are differences and where there are similarities between the fairness perceptions that the AI and HR condition illicit on participants. For example, we may not be able to capture significant differences on the job relatedness subscale, but we may find significant differences on another dimension like opportunity to perform. As such, the complete SPJS scale with all the procedural justice subscales as well as the general scale were used (see Appendix).

Interactional Justice

Related to the concept of procedural justice, people have a view of AI as accurate, but also lacking a personable element (Gray, Gray, & Wegner, 2007; see also Waytz & Norton, 2014). A recent paper by Lee (2018), for example, found that in jobs that require mechanical skills, respondents did trust algorithms to make better decisions than humans. However, in cases that require "human" (non-mechanical)

skills, respondents trusted algorithms less than humans and responded with more negative emotions to algorithmic decisions than human decisions. This may be because there is an underlying assumption that for non- mechanical skills, there is less opportunity to show other skills and abilities. Lee (2018) found that for the non-mechanical tasks, algorithmic decisions were perceived as less fair due to the algorithms' perceived lack of intuition, lack of subjective judgment capabilities, and lack of social recognition. This leads us to interpersonal qualities that people seek out in the hiring processes.

The *interpersonal treatment* grouping of procedural justice rules includes *interpersonal effectiveness, propriety of questions,* and *two-way communication*. Two-way communication refersto the opportunity that an applicant has to share their perceptions and reactions during the selection process. It occurs when the decision-makers are also involved in hearing and responding to feedback from applicants. Bies and Shapiro (1988) tested for this by grouping individuals in two conditions. The participants in the first condition were permitted to ask questions and raise opinions about the job and organization in a simulated interview. The participants in the other conditions, however, were not. The applicants in the first condition had higher perceptions of interpersonal justice. As such, participants who perceive that they could interact with the human decision-makers will view the process as fairer than those who interact with AI decision-makers.

H2: *Applicants who receive selection decisions from AI/ML procedure will have lower interactional justice perceptions than those applicants who received their decisions from human recruiters.*

In line with the hypothesis from this study, Gonzalez et. al, (2019) found that participants generally reacted less favorably on the interactional justice dimension to the AI decision-makers. The comments they received from the participants expressed concerns of its "impersonal nature and inaccuracy" (p.37). They went on to show that most of the participants particularly expressed stronger interpersonal concerns (e.g., dignified treatment, communication) than procedural concerns (e.g., consistency, accuracy). As such, it was also hypothesized that AI would have a significant effect on the interpersonal dimension of justice in addition to having lower procedural justice fairness perceptions.

In sum then, applicants who receive decisions from AI tools would perceive it as unfair because systems like these might take away applicants perceived ability to voice their opinions, appeal decisions and exert control (Gonzalez et al., 2019) and weaken perceived procedural fairness and interactional justice (Leventhal, 1980; Thibaut & Walker, 1975).

Distributive Justice: Outcome Favorability

While the procedures taken to administer selection processes are paramount, Gilliland (1993) emphasized that distributive outcome is "the most salient outcome" (p. 715) in determining fairness perceptions. Applicant reactions research has demonstrated that applicants who are not hired display negative fairness perceptions

in comparison to those who were hired (Bauer, Maertz, Dolen, & Campion, 1998; Hausknecht et al., 2004; Truxillo & Bauer, 2011). This is another major reason why fair procedures are particularly important for mitigating negative reactions to unfavorable outcomes such as rejections (Brockner & Wiesenfeld, 1996).

There could be several reasons why people could have a particularly negative reaction to being rejected by AI (instead of HR). Firstly, there may be a self-serving bias when the outcome is unfavorable (rejection), people attribute the outcome to the inadequacies of the process instead of their own performance (Schinkel et al., 2016). Gililand (1993) finds that when distributive rules are violated (negative outcomes), procedural justice rules have the biggest impact on fairness perceptions. That is, being rejected by an AI tool (rejection*AI) maybe more probable to elicit negative fairness reactions. Moreover, Schinkel, van Vianen, and van Dierendonck (2013) found that procedural fairness affected organizational perceptions when applicants were rejected. They further found that applicants who were hired appeared indifferent to procedural fairness. That is, when one is hired (despite perceiving the process as fair or unfair) it doesn't have a significant difference on the organizational attractiveness.

Another reason why rejection by an AI could lead to more negative fairness perceptions can be explained through the lens of fairness heuristic theory. It stated that that the novelty and people’s unfamiliarity towards AI, would likely heighten the feeling of uncertainty and thus their reliance on cognitive shortcuts which negatively impacts their fairness perceptions (Cropanzano, Byrne, Bobocel, & Rupp, 2001; Lind, Kray, & Thompson, 2001). Rejection by an AI could act like the shortcut/heuristic used to gauge the unfairness of the selection process.

Furthermore, Greenberg (2001) noted that unfavorable outcomes such as rejection will induce detailed analysis to infer fairness. This means that those applicants that are rejected especially by something as novel as AI will "more closely scrutinize selection information and perhaps engage in a more detailed attributional process" (Ployhart & Harold, 2004, p.90).

Therefore, while the researcher anticipated that those in the AI condition will have more negative fairness perceptions compared to having a human decision-make (H1); negative fairness perceptions would be amplified for those who are in the AI condition and whose outcome was rejection (outcome* condition). By the same token, those in the AI condition who receive a job offer would be more pacified and allayed due to the positive outcome (job offer). Thus, it is the researcher's hypothesis that outcome favorability will have a moderating effect on condition.

H3: *Outcome favorability will moderate the relationship between decision-maker condition and justice perception, such that the negative effect of having an AI decision-maker will be stronger when receiving an unfavorable outcome (rejection).*

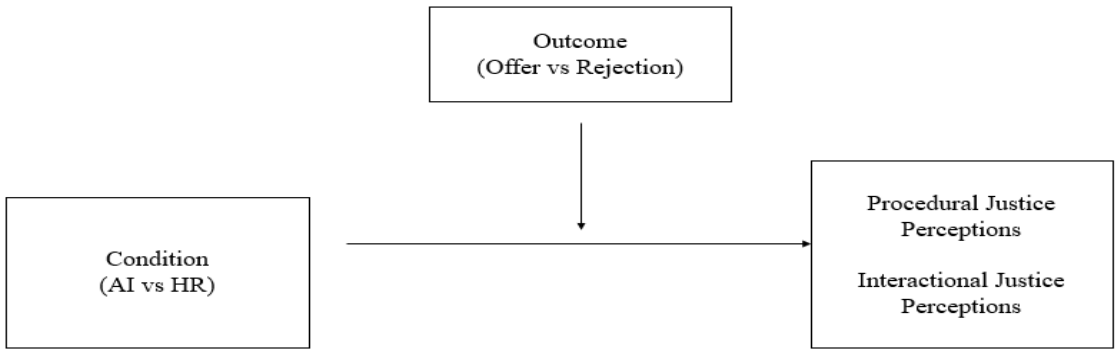

Figure 1. Moderation effect of outcome favorability on procedural and interactional justice perceptions

2) Race-based impression management.

The aforementioned Applicant Reaction theory (AR) has been expanded to include antecedents and moderators such as stage in the selection process, industry norms and job norms, market conditions (unemployment rate, job availability), individual characteristics (e.g., work experience, demographics, personality), and organizational context. Among these antecedents and moderators are applicant characteristics, such as personality, race, age, and so on (Fiske, 1998; Hausknecht et al., 2004). How these person-characteristics affect applicant perceptions of fairness is an important area to be explored since diversity in the workplace and in the applicant pool, has been on the rise (Mor Barak, 2015; Scarborough, Lambouths & Holbrook, 2019). Numerous organizations consider enhancing and maintaining workplace diversity as a core strategic value they have an obligation to promote (Mor Barak, 2015; Ng & Sears, 2012).

As such, one way to promote diversity starts with how we attract, recruit, and select applicants and ensure the application process is fair to one and all including those from minority groups, older applicants, and so on. In terms of selection, an application procedure may be perceived as unfair due to many reasons, such as those detailed above (e.g., low procedural justice).

However, another reason could also be the characteristics of the applicants themselves. This is because job candidates come to the selection context with experiences that influence their interpretation of the organization's selection processes and outcomes (Derous, Born, & De Witte, 2004). For instance, Ryan and Ployhart (2000) suggested that applicants' attitudes toward selection processes and procedures

might be influenced by their own past experiences and personal characteristics. Therefore, the perceptions they have of an application procedure can at least partly – be determined by the person-characteristics. For example, an individual who had prior experiences of discrimination may attribute a rejection decision to discrimination. This is especially the case for those with socially devalued/stigmatized identities who experience prejudice and discrimination in many realms of social interactions including the job application processes.

Often, to cope with stereotypes and prejudicial assumptions, stigmatized individuals will have certain ways of managing their identities to be viewed more favorably, for social mobility etc. These socially grounded impression management strategies are aimed at attenuating the impact of the social stigma, reactions and prejudices outgroups could have towards them (Roberts et al., 2008). However, research that focuses on the impression management used by different racial and ethnic groups during the hiring process is highly understudied warranting further investigation on the relationships among these variables. Thus, this section of the paper is guided by literature that addresses impression management of racial minorities in the workplace.

Impression management theory propounds that in order to be viewed more favorably, people employ identity management strategies whose primary purpose is to determine and establish one's standing in a certain social arena be it work, academia, etc. It is the effort of one individual to influence the impressions that are formed by others (Feldman & Klich, 1991; Gardner, 1992; Gardner & Martinko, 1988; Jellison, 1981). Out of the study of impression management, numerous other

theoretical constructs have emerged. One of these constructs is social identity-based impression management which examines impression management strategies that are based on one's membership to a particular social identity group, such as race or gender. Morgan (2002) defines social identity–based impression management as "one's cognitive awareness of how he/she is viewed by others as a member of his/her social-identity group in a given context" (Morgan, 2002, p. 22). They are aimed towards shaping the way others view oneself in terms of the social identity group one belongs to. That is, how we present ourselves to look favorable in the eyes of others and the perceptions we have of the social groups we belong in, are coupled together.

These socially grounded impression management strategies are aimed at attenuating the impact of the social stigma, reactions and prejudices outgroups could have towards minority groups (Roberts et al., 2008). In seeking to cope with negative stereotypes, social stigmatization, and group prejudices, individuals from minority groups attempt to control and establish others' perceptions and thereby control their outcomes whether that be getting that job, promotion, or other outcomes. For minorities in particular, the impact of stigma and negative stereotypes associated with their group identity will have a notable impact on career advancement prospects (Morgan, 2002). As such, they employ strategies to exert control over how they are viewed and affect their social and career standing which could include during job interviews and selection procedures for work.

One such social identity with various forms of social stigma associated with it is race. Racial identity can be defined as a "sense of group or collective identity based on one's perception that he or she shares a common racial heritage with a particular

racial group" (Helms, 1990, p. 3). Race-based impression management, which is a kind of self-presentation based upon one's membership in a race-based social identity group, is an integral part of how socially devalued minority individuals coordinate themselves at work and in other contexts (Morgan, 2002; Roberts, 2005; Roberts et al., 2008). It can be viewed as one offshoot of social identity management and are systematic attempts that individuals from stigmatized racial groups use to influence perceptions that others have of one's racial membership (Morgan, 2002). Therefore, those who belong in the minority racial group may want more opportunity to voice their concerns, use impression management and exert a sense of control over the application process. This ability to employ impression management may be found lacking in the AI condition. Furthermore, Bergsieker and Shelton (2010) went on to show that the different racial groups have divergent impression management goals.

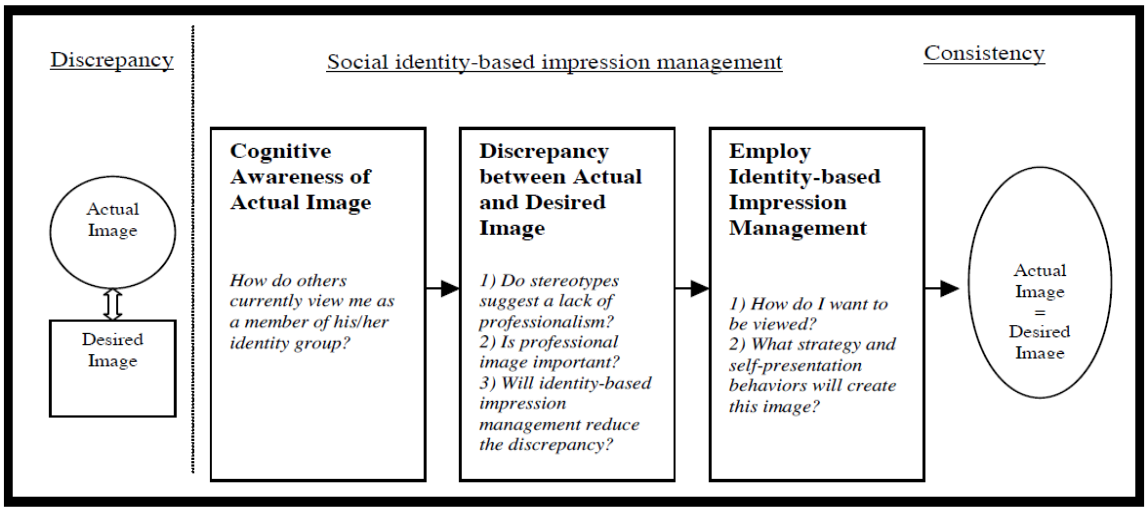

Figure 2. Morgan's (2002) conceptual model for social identity–based impression management.

In addition to the limited opportunity to manage impressions actively, another potential reason for the discrepancy in fairness perceptions between minority groups

and majority groups is the awareness that AI exhibits anti-Black bias such as in facial recognition systems and even recruitment (HBR, 2019). News reports of the potential biases of AI in facial recognition systems have been making headlines as well. For example, a study from the U.S National Institute of Standards and Technology (2019) examined 189 facial recognition algorithms and found that the majority of the algorithms falsely identified non-White faces. Fearing AI-enabling bias, some police departments have even banned their use (HBR, 2019).

AI, while promising less discrimination and more consistency in decision-making, has come under scrutiny recently as a potential enabler of bias. Rangita and colleagues (2021), sampled Black students and professionals and found that 40% of participants stated that they had job recommendations based on their identity instead of their qualifications. Furthermore, more than 20% stated that AI-based recruitment is a cause of worry. One of the biggest employers, Amazon, even had to discontinue an AI recruitment tool for its bias against women (HBR, 2019). News reports like these may be ingrained in the collective psyche of African Americans and thus, may have more sensitivity towards AI evaluations and recruitment.

More pertinently to this research, a study by Wallace and Clariana (2005) has revealed that women, older applicants, and African Americans have more difficulty using e-selection systems than members of other groups. Findings like this evince that, individuals from minority groups could have lower fairness perceptions to AI-based selection systems as well.

Based on the above literature and findings, this study posed the question of whether AI-generated decisions invoke similar reactions from minority groups. This

question was an important aspect of this study because individuals will have the perception of control over the interview, ask questions and engage in dialogue (impression management) with a human recruiter or decision-maker (Gonzalez et. al, 2019; Gilmore & Ferris, 1989). This propensity to use impression management during job applications may be more pronounced among minority racial groups who use race-based social identity management to secure certain outcomes.

As such, AI-based (non-Human HR decisions) would deprive minorities of this option of social identity-based impression management and hence their sense of control towards favorable outcomes. Moreover, recent news reports of AI-enabled anti-Black bias, and lack of familiarity with AI could create a sense of unfairness. Thus, individuals from racial minority groups may have lower fairness perceptions comparatively.

H4: There will be a three-way interaction between condition, outcome, and participant race such that, being rejected by AI would result in negative justice perceptions for African American participants compared to being rejected by HR.

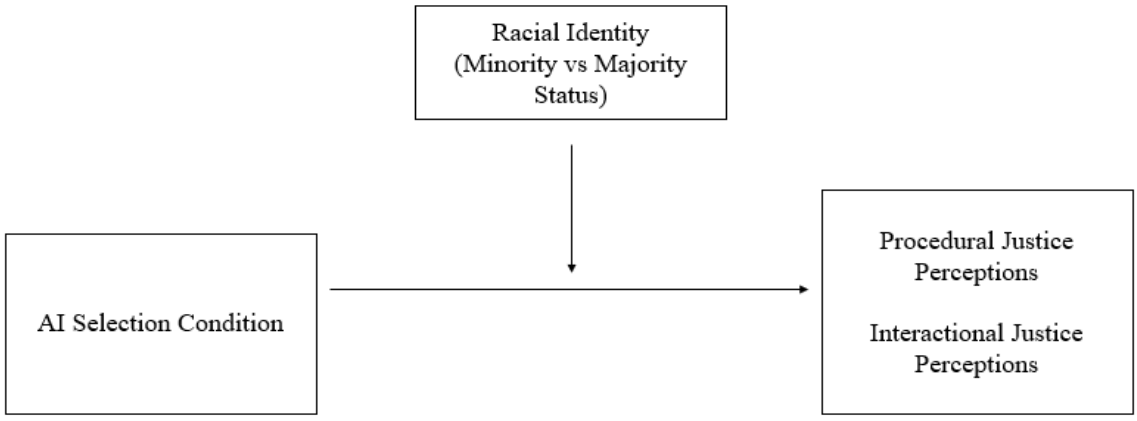

Figure 3. The hypothesized effect of Race on procedural and interactional fairness perceptions in the AI condition.

Chapter 3: Methods

Participants

Working adults that resided in the USA through Mturk were sampled. A total of 309 (178 female, 191 Black or African American, and 118 White participants) participated. 165 were randomly assigned in the AI condition and 144 in the HR condition. The first phase had a total of 550 participants. Due to attrition, we had a total of 377 participants who completed both the first and second phase. 68 participants were removed from analysis because they failed attention checks (either item) and/or did not complete the surveys (had lower than 70% completion rate).

Procedure

Data was gathered through MTurk (Turk Prime), which is an online amazon crowdsourcing marketplace that allows to outsource jobs and tasks to a distributed workforce virtually. In this case it was used to post a HIT job task (what MTurk calls its self-contained tasks), to simulate the typical job application process that occurs through online portals. The procedure consisted of two stages: 1) the application and 2) the post-application survey (longitudinal study). Prior to beginning the study, we invited potential MTurk participants to fill out pre-screen/pre-qualification questions that they believed might qualify them to complete a HIT. Participants were paid to fill out this initial screening but were made to believe it was an application that would allow them to make more money on a second task. In reality, there was no second HIT task. Instead, everyone was directed to a second HIT that contained survey questions about their experience. All participants received the same payment.

Participants applying for the fake HIT job post answered application blanks. The application blank items allowed participants to manage impressions by asking them to provide their strengths, weaknesses, and skills. Gilmore and Ferris (1989) noted that "in impression management terminology, this prior information (i.e., application blank or resume) available to the interviewer is typically strategic impression management" (p. 202). Moreover, application blanks are designed to collect information that an organization deems important for suitable hiring, thus maintaining fidelity. All participants were also asked to provide their work experiences, as well as demographic information. After 24 hours, they were sent links to the second phase of the study, where they were randomly assigned to a condition (AI vs HR) and outcome (rejection vs acceptance) groups. The message either read:

"Your application was reviewed by a [human resources manager/AI system]. We would like to inform you that you have been accepted to complete the HIT job you have applied for. Before proceeding to the task, there are surveys to be filled about the job application process. Please press next to continue.

Or

"Your application was reviewed by [Human resources personnel/Artificial Intelligence] tool. We regret to inform you that you have been rejected to complete the HIT job you have applied for. However, you will be paid $1.00 for completing the surveys about the job application. Please press next to continue.

After this, they filled out surveys, got debriefed and were compensated for completion.

Measures

General Applicant Reactions

General Applicant Reaction Scale measures the overall perception of fairness of the job application process and has a reliability of (α = .75).

Procedural Justice

The Selection Procedural Justice scale (SPJS) is composed of procedural justice dimensions such as opportunity to perform (α = .94), reconsideration opportunity (α = .89), and job-relatedness (α = .83), information known (α = .92) and feedback (α = .82).

Interactional Justice

For interactional justice, the social higher-order factor subscales of the SPJS were used. It measures how participants assessed the interactional component of the job application process, and it has a reliability of (α = .92).

Emotional Reactions Scale

Participants completed items assessing the extent to which they experienced various emotional reactions (Gonzalez et al., 2019) during the process such as being anxious, angry, hopeful, excited, worried, skeptical, trusting. Negatively valenced items were reverse-coded and the scale was combined to create an overall measure of emotional reactions (α = .91), with higher values indicating more positive emotional reactions.

Familiarity with Artificial Intelligence

Familiarity with AI was believed to affect how fairness was perceived (Johnson & Verdicchio, 2017). To measure this, the researcher utilized an instrument

adapted from Gonzalez et al. (2019) that probes the extent of familiarity of participants towards AI. Reliability for the scale was (α = .85).

Qualitative Items

In addition, qualitative data was collected to add more depth to the quantitative findings. Participants were asked the following questions:

1. Would you rather be evaluated by AI or HR personnel and why?
2. What factors lead to your level or comfort or discomfort in the AI selection system?

Chapter 4: Results

A three-way MANCOVA was conducted with the following predictor variables: Decision Condition (AI = 0, HR = 1), Participant/ Applicant Race (Black = 0, White = 1) and Outcome (Rejected = 0, Accepted = 1). The dependent variables included: general fairness perceptions, *interactional justice*, dimensions of procedural justice perceptions: *job relatedness, information known, chance to perform, reconsideration opportunity, feedback. familiarity with AI* was included as a covariate. Emotional reactions was also measured to gauge participants' emotions. There was significant interaction found between Condition, Outcome and Race at (Pillai's V = 0.95, F (9, 265) = 3.083, p = .002, partial η2 = .095)

In addition, a post hoc sensitivity analysis given power of .80, three predictors and a sample size of 309 garnered an effect size of f^2=0.03.

Hypothesis 1: Procedural Justice

Our first hypothesis (H1) was that Applicants who receive selection decisions from AI/ML procedure will have lower perceptions of opportunity to perform, feedback, reconsideration opportunity and lower general procedural justice than those applicants who received their decisions from human recruiters. The findings show that condition by itself (being in the AI or HR condition) did not have a main direct effect on any of the procedural justice dimensions. Thus, H1 was not supported.

Hypothesis 2: Interactional Justice

Our second hypothesis (H2) stated that Applicants who receive selection decisions from AI/ML procedure will have lower interactional justice perceptions than those applicants who received their decisions from human recruiters. There was a significant main effect of condition (AI vs HR) on interactional justice, F (1, 277) = 4.13, p = .036, such that participants in the AI condition had lower interactional justice scores (M = 3.40) than those in the HR condition (M = 3.65). Therefore, H2 was supported.

*Hypothesis 3: Condition * Outcome*

We then hypothesized (H3) that Applicants will have more negative procedural and interactional justice perceptions when evaluated by AI compared to HR, particularly when they are rejected. To test this hypothesis, we carried out a two-way MANOVA between condition and outcome. In line with H3, the interaction between condition (AI vs HR) and outcome (rejection vs acceptance) had a significant effect on some of the procedural justice outcomes such as: chance to

perform, reconsideration opportunity, feedback, general procedural reactions and interactional justice perceptions.

The interaction between condition and outcome (either got accepted or rejected) had a significant effect on the chance to perform dimension of procedural justice, $F(1, 276) = 4.01$, $p = 0.04$. A pairwise comparison of the marginal means indicates that participants in the AI condition who were rejected had lower perceptions of chance to perform (M=2.90) than those rejected by the HR condition (M=3.19, p=0.08). Those who were accepted in the AI condition had a mean of (M=3.38) compared to those who were accepted by HR (M=3.14, p=.81), which was not significant.

The interaction between condition (AI vs HR) and outcome (rejection vs acceptance) had a significant effect on reconsideration opportunity, $F(1, 276) = 5.27$, $p = 0.028$. A pairwise comparison of the marginal means indicates that participants in the AI condition who were rejected had lower perceptions of reconsideration opportunity (M=2.49) than those rejected by the HR condition (M=2.90, p=0.03). Those who were accepted in the AI condition had a mean of M=3.00 compared to those who were accepted by HR, M=2.82, p=0.634, which was not significant.

Feedback dimension was also significantly affected by this interaction [F (1, 277) = 8.45, p =0.003]. A pairwise comparison of the marginal means indicates that participants in the AI condition who were rejected had lower feedback perceptions (M=3.17) than those rejected by the HR condition (M=3.77, p=.001). Those who were accepted in the AI condition had a mean of (M=3.73) compared to those who

were accepted by HR (M=3.51, p=0.132), showing that this effect was only significant when rejection occurs in the AI condition.

General procedural justice was also significantly affected by this interaction [F (1, 277) = 7.23, p =0.008]. A pairwise comparison of the marginal means indicates that participants in the AI condition who were rejected had general procedural fairness perceptions of M=2.74, which is significantly lower than those rejected by the HR condition (M=3.02, p=.000). Those who were accepted in the AI condition had a mean of (M=3.10) compared to those who were accepted by HR (M=3.02, p=0.982), yet again showing that this effect was significant when rejection occurs in the AI condition.

Condition and Outcome: Interactional Justice

There was also a significant interaction effect between condition and outcome on interactional justice [F (1, 277) = 7.69, p = .003]. A pairwise comparison of the marginal means indicates that participants in the AI condition who were rejected had lower interactional justice scores (M=3.02) than those rejected by the HR condition (M=3.72, p<0.001). Those who were accepted in the AI condition had a mean of (M=3.67) compared to those who were accepted by HR (M=3.59, p=0.434), which was not significant.

This further indicated that rejection (outcome favorability) in the AI condition is more important than acceptance in either condition. Overall, H3 was supported. Outcome of a decision colors what is perceived as fair in the AI condition, where rejection foments lower scores across many dimensions of procedural justice and interactional justice.

Independent Variable	Dependent Variable	Sum of Squares	df	Mean Square	F.	Sig
Outcome * Condition	Interactional Justice	11.849	1	11.849	13.628	.000
	General Reactions	2.332	1	2.332	7.233	.008
	Job Relatedness	5.808	1	5.808	6.619	.011
	Information Known	.257	1	.257	.217	.642
	Chance to Perform	4.979	1	4.979	4.015	.046
	Reconsideration Oppo.	5.714	1	5.714	5.276	.022
	Feedback	10.784	1	10.784	11.641	.001
	Emotions	25.733	1	25.733	19.348	.000

Table 1. outcome * condition effect on dependent variables.

Hypothesis 4: Condition* Outcome * Race

Our fourth hypothesis (H4) was that Black participants will report lower fairness perceptions, especially on the AI-generated decision than their White counterparts when rejected.

The three-way interaction effect was significant for general procedural justice reactions, [F (1, 276) =3.89, p<0.001]. A pairwise comparison of the marginal means indicates that Black applicants in the AI condition that were rejected reported lower procedural justice reactions (M=2.62, p<0.001) than those who were rejected in the HR condition (M=3.08, p<0.001). A pairwise comparison also showed that Black participants that were accepted in the AI condition reported higher procedural justice

reactions (M=3.25, p=.037) than those who were accepted in the HR condition (M=3.00, p=0.037).

There was no significant effect for White applicants in either condition and outcome. In the AI condition White participants who faced rejection had a marginal mean of 2.99, whereas in the HR condition and rejected, they had a mean of M=2.94, p=0.733. They had a marginal mean of M=2.83 when accepted in the AI condition while those who were accepted in the HR had a mean of M=3.04, p=0.151.

There were no significant pairwise comparison differences for White participants in the HR condition who were rejected, had a mean of M=3.83 and those who were rejected in the AI condition who had a marginal mean of M=3.45, p=.143. White participants in the AI condition who got accepted had a mean of M=3.49 compared to being accepted in the HR condition at 3.57, p=0.753.

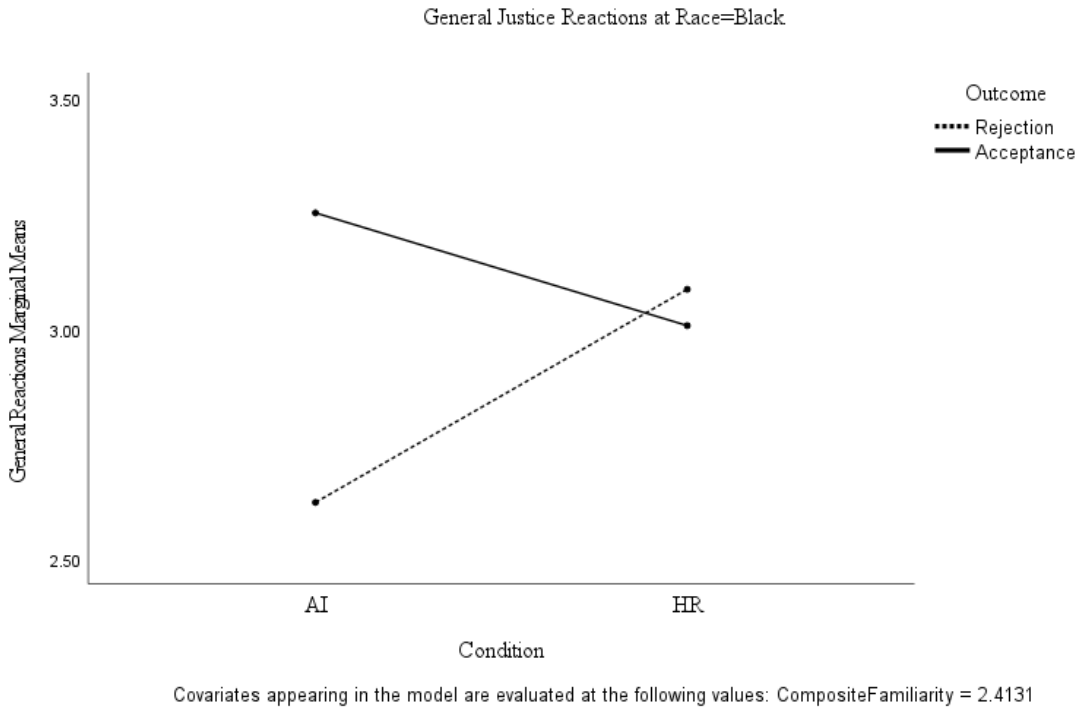

Figure 4. General Justice Reactions by Condition and Outcome at Race=Black

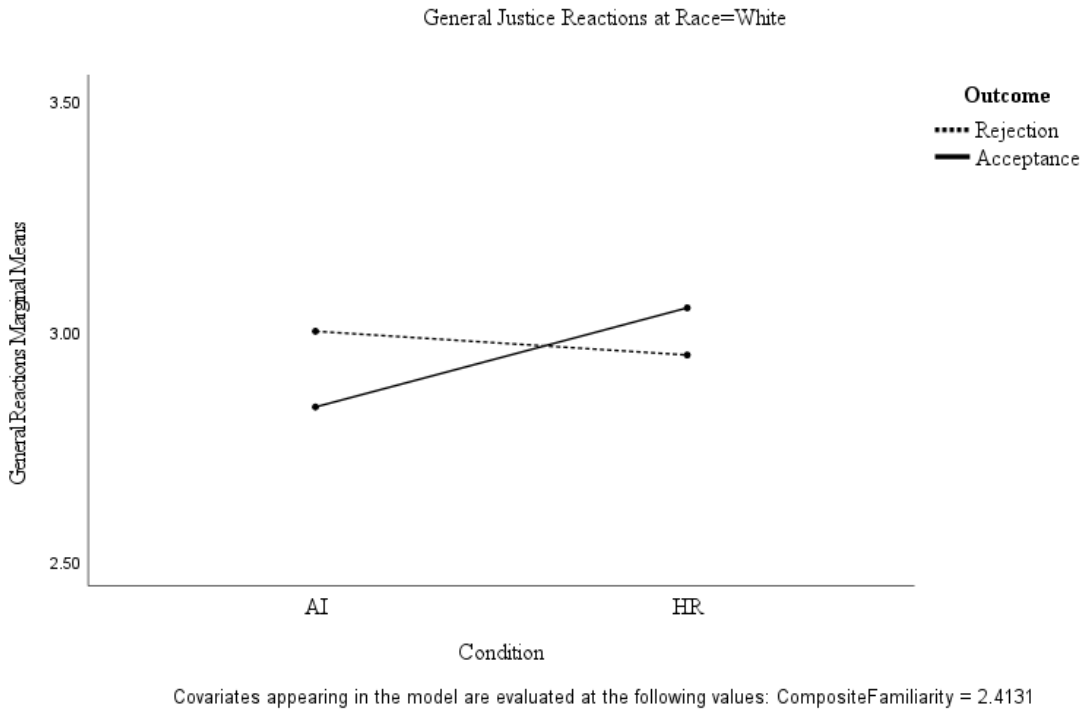

Figure 5. General Justice Reactions by Condition and Outcome at Race=White

Exploratory Findings:

To gauge how people reacted in the conditions during the application process, an emotional scale adopted by Gonzalez et al., 2019 was included in the second phase of the survey. Furthermore, other dimensions that were not hypothesized to be affected yielded some significant results:

Job Relatedness impacted by Condition* Outcome:

While it was not a hypothesis of this study that condition (AI vs HR) and outcome (acceptance vs rejection) would affect the job relatedness dimension of procedural justice, the interaction between condition (AI vs HR) and outcome (rejection vs acceptance) had a significant effect on some of the procedural justice

outcomes such effects on the job relatedness dimension $F(1, 276) = 6.62$, $p = .0.01$. A pairwise comparison of the marginal means indicates that participants in the AI condition who were rejected reported lower job relatedness (M=3.58) perceptions than those in the HR condition (M=3.92, $p = .039$). There was no significant difference in job relatedness perceptions between those accepted in the AI condition (M=3.76) and those accepted by HR (M=3.63, $p = .411$).

Emotional reactions during the application process:

Condition and outcome had a significant effect on emotions [F (1, 277) = 17.11, p <0.001]. A pairwise comparison of the marginal means indicates that participants that were in the AI group and rejected had more negative emotions *(M*=2.95*)*, than those who were rejected in the HR condition (M=3.64, p<0.001). The marginal means also indicates that participants that were in the AI group and accepted had more positive emotions *(M*=3.72*)*, than those who were accepted in the HR condition (M=3.37, p=0.03). This also shows that rejection in the AI group is where the most negative emotional reactions towards the application process occurs.

This three-way interaction between race, outcome and condition had a significant effect on emotional experience, [F (1, 276) = 8.46, p=0.003] during the application procedure. A pairwise comparison of the marginal means indicates that Black applicants rejected in the AI condition reported less positive emotions (M=2.48, p<0.001) than those who were rejected in the HR condition who had a marginal mean of (M=3.44). Black applicants had a marginal mean (M=3.95) when accepted in the AI condition versus when accepted by HR they had a mean of (M=3.18, p<0.001).

Qualitative Findings

The purpose of the qualitative questions was to help contextualize the quantitative findings and supply answers that the quantitative measures were not able to capture. It is a form of triangulation that can help us elaborate or expand on the findings of the quantitative method (Creswell, 2007).

The process for the thematic analysis follows the guidelines suggested by Braun and Clarke (2006). The researcher started with familiarizing herself with the data and assessed frequently used words and sentiments. This was followed by the generation of an initial coding scheme based on those observations and formed 6 content themes (personhood, communication, bias, efficiency, trust, techy). Then, the researcher and three other RAs coded the qualitative answers in terms of the extent to which each answer fit a given theme. Coders used a 5-point Likert scale indicating the strength of that theme's presence in a given answer. ICC were generated for the themes. ICC values indicate sufficient levels of consistency across raters, with the lowest ICC value being 0.67. Two themes with lower ICC scores were dropped (Trust and Efficiency).

Question 1: Who would you rather be evaluated by? Why?

The first question asked participants if they would choose to be evaluated by (AI vs HR) and why. People overwhelmingly chose to be evaluated by human resources personnel (HR=216, AI=69). The reasons they gave for their choice was organized around six themes that were identified during reading of the comments and theme extraction. These six themes emerged as reasons for their preference. Participants mentioned multiple reasons in their comments that were then evaluated

for extent of presence on a 5- point likert scale (ranging from non-existent, to highly present of each of the six themes.).

Table 2. Themes for applicants' preference of evaluation system

Theme	ICC	Means	Example Quotes
Personhood: Understand holistic personality; the characteristics, quirks and nuances of a person; reductionism	.823	HR→(M=3.28); AI→ (M=1.12)	- "I would choose the recruiter because a human can detect intangible qualities that a candidate may have."
Communication: The ability to speak, get spoken to and get feedback, interact, influence, show and perceive emotions, flexibility and empathy	.776	HR→(M=3.0) AI →(M=1.26)	-"I would rather have a human as people can be swayed. An AI does not have any room to be influenced."
Bias: It dealt with sentiments of existence of discrimination, ideas of fairness and exclusion	0.93	AI→ (M=4.24); HR→ (M=1.31).	"Algorithm because as humans it is a high chance for personality bias when skill trumps personality. The AI would not have personality bias."
Techy: Too programmed, formulaic, rigid, cold, having fixed criteria, being prone to failure, faultiness	.657	AI→M=1.92; HR→(M=1.09)	"AI would be judging based on whatever criteria that the programmer made, but if a real person were to review my resume there's a chance that the person would judge differently."

1. Personhood:

This theme was the most mentioned. The inter-rater reliability for this theme (ICC =.823), was sufficient (See Table 2). Many of the participants felt apprehensive of AI/ML because as this theme showed, applicants perceived that AI would not do their multifaceted personalities justice. They thought it would be reductionist and would not understand their characteristics and quirks the same way a HR personnel would. Those who chose HR were more likely to cite reasons grouped under the "personhood" theme which includes: the ability of HR to understand holistic personality; the characteristics, quirks and nuances of a person. Many stated that AI reduces the person to some criteria instead of holistically.

For example, one participant said:

"I would choose the recruiter because a human can detect intangible qualities that a candidate may have." While another applicant said that he "would prefer a human. The AI cannot discern soft skills which are arguably more important in some professional experiences than hard skills and specific experiences."

Here for example, they mention that HR would be better at assessing soft skills while AI misses this element. Thus, this theme emphasized that applicants will be reduced to a set of criteria that would overlook their quirks and soft skills.

2. Communication:

This was the second most mentioned theme as the reason for participants choosing to be evaluated by a HR professional (ICC=.776). The mean for those who chose HR was M= 3.01 for this theme and M=1.26 for those who chose AI. This theme had keywords such as having the ability to speak, get spoken to, getting

feedback, interaction, ability to read emotions, flexibility, and empathy. We also identified that there were pervasive expressions of having the ability to direct/change the outcome/influence through communication.

For example, one participant wrote, “I would rather have a hiring decision made by a manager because I can charm the manager.” An African American participant stated that “I would rather have the human. The AI cannot be manipulated or impressed.”. Further illustrating this feeling of having control over outcomes was an African American participant who stated that “[he] would rather have a human as people can be swayed. An AI does not have any room to be influenced”. Most believed that the element of human interaction would give them a chance to impact the outcome through means of influence, charm, improvisation and so on. While the means among the White (M=2.5) and Black participants was similar for this theme, African Americans (M=2.64) cited communication a bit higher for their level of discomfort towards an AI evaluation system. This in some way lends credence to Roberts et al., (2008) paper on race-based identity management where she argued that the need to impression manage and influence perception of ourselves is heightened among African Americans.

As some of these quote’s show, participants choose HR personnel to have influence on the decision making and sway decision making. As reiterated above, applicants may perceive less control over their outcomes when they are evaluated by AI because there may be fewer opportunities to appeal decisions, express opinions, or manage impressions (Gonzalez et al., 2019). This lack of opportunity for impression management has been expressed by participants stating that there will not be room to

influence, sway, improvise, charm and engage in other impression management strategies.

Even though there were not as many people that chose AI, those who did stated that they would choose AI because of its lack of emotionality and ability not to be swayed by emotional decisions. For example, a participant stated, “I would rather have a hiring decision made about me be made by an AI algorithm because that decision would be free of emotion. With a human decision-maker, emotion almost always enters into the decision.”

3. Bias:

Inter-rater consistency for this theme was sufficient (ICC= 0.93). This theme was also among the common reasons mentioned for participants’ choices, especially for those whose choice was an AI system, M=4.24 versus those who chose HR M=1.31. It dealt with sentiments of existence of discrimination, ideas of fairness and exclusion.

Bias/fairness was perceived differently based on whether people’s choice was AI or HR. Those who chose HR thought AI would be biased because it would lack a personal element, empathy and the lack of interaction. For example, a participant who chose HR said he would rather be evaluated by a recruiter “because you can easily tell from their facial impressions if they were biased or not.” Another participant also thought that relegating selection and evaluation to an AI only would be unfair stating “I'd rather have the hiring decision being made by a recruiter/hiring manager. Human interaction is essential in making these decisions, and having computers decide, is unfair to the candidates. AI should be used as an aid in making hires.”

However, those who chose AI said objectivity, the lack of these emotional and interactional elements made it fairer and less biased. One participant said he preferred an “Algorithm because as humans it is a high chance for personality bias when skill trumps personality. The AI would not have personality bias.”. Another one stated that he “would rather have the hiring decision made by an AI algorithm as [he] think it would be a lot more fair and unbiased.”

Those who chose AI claimed that AI would be less biased, more logical and more “information-oriented than people are.”. However, those participants that preferred HR and whose comments fell under this theme of bias, revealed concerns of the inaccuracy of AI/ML. They questioned if AI was free of bias, its tendency to be impacted by a human coder etc.

This is surprising because while many whose choice was AI stated lack of bias to be their primary reason for their choice, those who chose HR did not consider AI to be accurate and standardized and viewed AI as likely prone to biases as well.

4.Techy:

The ICC for this theme was slightly lower than acceptable, ICC =.657. As such, conclusions should be drawn tentatively. This theme subsumed elements of AI being programmed, formulaic, rigid, cold, and having unclear criteria. This theme meshed somewhat with the Personhood theme which expressed that AI won't be able to grasp nuances and characteristics of the person. This theme was different in that people pointedly emphasized AI’s robotic and inflexible nature. One participant stated that they would choose a recruiter because the “AI would be judging based on

whatever criteria that the programmer made, but if a real person were to review my resume there's a chance that the person would judge differently."

Another person who had some familiarity with how an AI works chose to be evaluated by a recruiter because "I understand how computer programming and artificial intelligence works. There are cultural values, traits, tendencies, and simple things you cannot hard code into an algorithm that will not be detected and means the AI will make a calculated choice but will be missing many factors."

Another person stated that jobs were of such importance that they should not be left for an AI to exclusively make the decision. He stated that hiring decisions should be made "by humans and humans only. Things that can greatly impact a person's life such as getting hired for a job, should never be made by AI."

In sum, for the question of what participants would choose to be evaluated by, most choose HR personnel (HR=216, AI=69). Those who chose HR were also more likely to cite reasons grouped under the *person hood* and *communication* themes, compared to those who chose AI. Those who chose HR were also more likely to give responses that AI was "Techy" (e.g., too programmed, formulaic, rigid, cold, having fixed criteria, and being prone to failure and faultiness compared to those who preferred AI. Those who chose AI were more likely to cite reasons grouped under the "lack of bias" theme, which included perception of AI discriminates less and is fairer.

Question 2: What factors affect your level or comfort of discomfort with AI?

This question specifically asked what factors led to the comfort or discomfort of participants in regard to being evaluated by an AI. Many of these themes are related and are interconnected. The themes we got from this data were as follows:

Table 3. Themes for applicants' comfort/discomfort with AI:

Theme 2	ICC	Example Quotes
Personhood: Understand holistic personality; the characteristics, quirks and nuances of a person; reductionism	.838	- "heart, determination, devotion, desire and conscientiousness are qualities that an AI may not recognize. A pleasant and professional demeanor may not be recognized."
Trust: - AI's potential to bring forth privacy issues, data usage and transparency of such systems.	812	-"privacy would be of concern. Is it just one more thing documenting everything we do?"
Bias: It dealt with sentiments of existence of discrimination, ideas of fairness and exclusion	0.937	- "I feel more comfortable that the AI would make unbiased decisions based on everyone being treated equally"
Communication: The ability to speak, get spoken to and get feedback, interact, influence, show and perceive emotions, flexibility and empathy	0.752	-"I will not influence AI in to giving me a job"
Techy: Too programmed, formulaic, rigid, cold, having fixed criteria, being prone to failure, faultiness	.661	"AI is algorithms and mathematical formulas, and that makes them cold and uncaring."
Technology progress: The effectiveness/accuracy of AI is questioned along with the criteria it used for the selection of applicants.	.622	-"AI will only do what it was programmed to do. So is the program is biased, it will produce biased decisions"

1. **Personhood:**

The ICC of this theme was .838. This was the most frequently mentioned theme. Participants questioned the capabilities of AI to grasp the full personhood, quirks and nuances of the person. These meshed with another emergent theme (Robotic) which stated that AI is too formulaic and may remove out participants because of how formulaic and exacting it could be. Participants stated that most of their discomfort emerged from the lack of AI to understand humor, human emotions, intuition, and perceived inability to create a holistic view of the person.

For example, one participant stated that "heart, determination, devotion, desire, conscientiousness are qualities that an AI may not recognize. A pleasant and professional demeanor may not be recognized. A team-player or individual creativity may not be recognized. But these could be discussed with or seen by a human." Another participant stated that he doesn't "want to be just data to a company that is looking to hire someone. I am a person not a set of data for AI to read and choose." As such, a major reason for the level of discomfort in being evaluated by an AI was the perception that AI would be too reductionist, not be able to understand unique human qualities and its perceived lack of grasp on soft skills a person brings to the table.

2. **Trust:**

The ICC for this theme was .812. Here participants stated that their discomfort of AI stems from its possible privacy invasion issues, data usage and transparency that AI would entail.

One participant stated that "there are different hacking into systems and security

breaches. And you can't trust machines to do what a human can do." Another participant stated that "privacy would be of concern. Is it just one more thing documenting everything we do?" Thus, safety of data, misuse by organizations and privacy was another reason given for their discomfort of AI.

3. Bias

The ICC for this theme is .937. Both groups, those who wanted AI or did not want to be evaluated by AI cited bias as a major concern for their level of discomfort in AI evaluation.

Those who said their major reason for being comfortable with AI is its ability to mitigate bias and stated that it would treat everyone fairly. For example one participant said "I feel more comfortable that the AI would make unbiased decisions based on everyone being treated equally." Another participant stated "I am comfortable with AI because it is fair, I think that AI is too unbiased and honest" Some participants also mentioned that an AI won't have preconceived notions of a person based on how they look and sound, thus making them less biased. Along these lines one participant said that "I know the AI will not have prejudice because of my age, gender, skin color, tattoos, and other stand-out features."

However, those who said their major discomfort with AI is because of its proneness to bias stated that AI could easily be programmed to have bias and that it would perpetuate human mistakes on a larger scale. For example, one participant said that he was uncomfortable with AI hiring because "a lot of AIs have a bias against people of color when using facial recognition software.". Another participant gave similar reasoning stating that "I feel that algorithms can sometimes make more

discriminatory and biased selections than humans.". Yet another participant stated that they worry "about the prejudices of the people behind the AI" and that they "can't negotiate with the AI and it can't temper its attitude towards [them]."

4. **Communication**

The ICC for this theme was .752. This theme emphasized the inability to impression manage and to have an opportunity to perform and impact/sway the decisions by the AI. It also had themes of feedback, posing questions and interactions. This was given as a major reason for discomfort towards an AI system. One participant put it tritely saying, "no way to sway an AI."

Another stated that their discomfort was in "not being able to talk to an AI into giving [them] a job". Another added that he is "worried that the guidelines an AI would operate within are too strict, and therefore there is no wiggle room at all."

Most perceived AI as lacking two-way communication and a feedback system. Furthermore, the lack of opportunity to influence/sway and or change outcomes of a decision were given as major reasons for discomfort towards an AI based evaluation. One participant said that they think the process would be "so cut and dry and determined by factors out of my control.". Another one stated that while they like that, facts matter for an AI "you can't talk yourself into a job with an AI." These statements hint at the need to manage impressions, the ability to sway and have a degree of control over the decision-making process.

5. **Techy:**

The ICC for this theme was .661. Participants mentioned their comfort or discomfort with AI has to also do with its computerized nature, lack of interaction,

coldness and AI being formulaic. It underscored the robotic and formulaic nature of AI.

For example, one participant said that “an AI only knows what it's programmed to do. There is no human factor for understanding context and meaning.”. Another also stated that AI technology is based on “algorithms and mathematical formulas, and that makes them cold and uncaring.”

6. Technology progress:

The ICC for this theme is .622. Numerous participants questioned the effectiveness and accuracy of the AI, what criteria it uses for the selection and questioned if the technology is developed enough to rely on AI for selection of employees. For example, one participant stated that “without knowing exactly how the algorithm functions, there is no way to understand the flaws of the end result.” Another participant also alluded to the garbage in, garbage out phenomena of AI stating that AI “will only do what it was programmed to do. So, if the program is biased, it will produce biased decisions.”.

A different participant claimed that knowing what factors are considered in the algorithm would increase their comfort with AI stating that “AI is only as good as the parameters that it has been given, and I don't think we are at a point that we can program an AI to make the intuitive leaps that a human is capable of.”

In terms of comfort with AI, people cited that they like it for its lack of bias, but this was qualified in that as long as the criteria set is correct or programmed accurately. This was further qualified by comments suggesting that AI should have a human touch and ability for feedback.

Chapter 5: Discussion

This study aimed to assess how applicants react to being evaluated by artificial intelligence (AI) versus a human resource personnel (HR) using a realistic application scenario.

Consistent with Gonzalez's (2019) study, the researcher did not find significant main effects on procedural justice among the conditions but did find a main effect for interactional justice. This supports Gonzalez's reasoning that AI takes away the interpersonnel element from the application process rather than procedural justice elements. Similar to their findings, participants expressed mostly interpersonal concerns such as communication rather than procedural concerns (e.g., consistency, accuracy) in the qualitative comments they gave as well, bolstering the quantitative result.

However, AI evaluation had a negative effect on some procedural justice perceptions when the outcome was rejection (i.e. it depended on the outcome favorability). For example, the significant interaction effects of outcome by condition showed that those who were in the AI condition and got a rejection reported more negative perceptions of job relatedness, and feedback, compared to those rejected in the HR condition. This moves beyond past research in that being evaluated by an AI can have negative effects on some dimensions of procedural fairness (job relatedness, reconsideration opportunity and feedback) and general fairness reactions, but only when the individual is rejected by AI. Participants were more likely to report that the procedure was not job related enough, thus questioning the validity of the tests/surveys used. Differences in perceptions of reconsideration opportunity and

feedback perceptions also show that those rejected by an AI see the procedure as lacking a way to communicate and that their chances of appealing the process and decision (reconsideration opportunity) are low.

This relates to past research that shows that outcome favorability moderates between justice rules (such as procedural justice) and the individual's reaction to a hiring decision (Gilliland, 1993). The reason why people have a particularly negative reaction to being rejected by AI (instead of HR) could be many. For one, there may be a self-serving bias when the outcome is unfavorable (rejection), people attribute the outcome to the inadequacies of the process instead of their own performance (Schinkel et al., 2016; Ployhart & Harold, 2004; Ryan & Ployhart, 2000). That is, people's sense-making mechanisms of negative outcomes come to play (Brockner & Wiesenfeld, 1996). For events that are unexpected and negative (such as rejection) external cues and processes are weighed more heavily. Gililand (1993) finds that when distributive rules are violated (negative outcomes), procedural justice rules have the biggest impact on fairness perceptions. Building on this Schinkel, van Vianen, and van Dierendonck (2013) found that procedural fairness affected organizational perceptions when applicants were rejected. Surprisingly, they found that applicants who were hired appeared indifferent to procedural fairness. That is, when one is hired (despite perceiving the process as fair or unfair) it does not have a significant difference on the organizational attractiveness. They concluded that for those who are rejected, fairness of the procedure is very influential in determining their perception towards the organization unlike those hired.

Another explanation for this finding could be that applicants have cognitive shortcuts or heuristics about justice perceptions in uncertain situations (Cropanzano, Byrne, Bobocel, & Rupp, 2001; Lind, Kray, & Thompson, 2001). Given the novelty and people's unfamiliarity towards AI, this would likely heighten the feeling of uncertainty and thus their reliance on cognitive shortcuts which negatively impacts their fairness perceptions. This is known as fairness heuristic theory which states that people construct a 'fairness heuristic'. They use this fairness shortcut to guide their reactions and expectations in ambiguous and unfamiliar situations such as being evaluated by AI. (McCarthy et al., 2017). Here, rejection by an AI was the shortcut/heuristic used to gauge the unfairness of the selection process. Greenberg (2001) notes that unfavorable outcomes such as rejection will actually induce detailed analysis to infer fairness. This means that those applicants that are rejected especially by something as novel as AI will "more closely scrutinize selection information and perhaps engage in a more detailed attributional process" (Ployhart & Harold, 2004, p.90). Fiske and Taylor (1991) also note that conditions that are goal relevant, violate expectations or are novel are regarded as more salient. What this means is that negative events (such as rejection) will be perceived more negatively than favorable events because they strongly violate expectations in addition to the novelty of AI.

Thus, negative fairness perceptions were amplified for those who were in the AI condition and who were rejected. Rejection in the AI condition negatively affected fairness perceptions such as interactional justice, job relatedness, feedback, and emotional reactions.

Qualitative results indicate another reason why rejection in the AI condition may have led to negative fairness perceptions on both interactional and procedural justice (job relatedness, reconsideration opportunity and feedback dimensions). The lack of human presence could serve participants as a heuristic for job relatedness since interpersonal dynamics of selection (such as interview) maybe considered relevant for a job (Van Iddekinge, Raymark, & Roth, 2005). Thus, the lack of a human resources personnel throughout the process may have impacted why rejections in AI led to a lower score on the job relatedness dimensions. Reconsideration opportunity and feedback are the other two dimensions that were affected by the outcome*condition interaction. This may be due to again the uncertainty and novelty of AI, and their reliance on fairness heuristics which leads them to perceive a limited opportunity (chance) to express themselves to this AI. The qualitative findings lend credence to this. People seek to impression manage and self-promote and have a degree of influence over the outcome. Perhaps participants rejected by AI felt that AI robbed them of this chance to impression manage and then subsequently perceived it more negatively. As the qualitative data showed, most of the participants stated that they won't be able to influence, sway and charm the AI and thus change the outcome. Thus, rejection by an AI is not only detrimental to interactional justice perceptions but also to procedural fairness perceptions.

In sum, there seems to be an ambivalence towards AI, and it seems like rejection (outcome favorability) is what makes participants infer fairness. Reasons why there is not low procedural fairness evaluations by those hired in the AI group (unlike those rejected in the AI group) could be two-fold. One, acceptance makes one feel

indifferent about AI due to the initial ambivalence towards AI, while those rejected (who initially are also ambivalent about AI) infer unfairness from that outcome (being rejected). Second reason could be that being accepted by a novel technology such as AI leads to a boost in self esteem that goads the individual to fall for attribution bias. That is, those who are accepted by an AI are more likely to attribute their acceptance to their skills/personality and overlook the procedural pitfalls (the environment) they had faced during the application process.

On a different note, results from this study indicated that there are also some differences in fairness perception based on participant race (main effect). Compared to White participants, African American participants reported more negative perceptions of procedural justice. This finding may hint at the fact that African Americans, and others with stigmatized identities, seek out more feedback in order to impression manage (Roberts et al., 2008). African American participants also reported more negative emotions in reaction to this application process, compared to their White counterparts. This could be due to past experiences of job discrimination that influence the perceptions of the application process. African Americans seem to be highly alert to this experience and may explain why they have low feedback, justice perceptions and negative emotional experiences (Ryan & Ployhart, 2000). The applicant attribution reaction theory (Polyhart &Harold, 2004) states that attributional processing occurs between an event such as administrator of a test and the formation of fairness perceptions. When an event is stressful, important, novel or unfavorable, attributional search is prompted (Wong &Weiner, 1981). These conditions are inherent in selection context and heighted in the context of AI selection. Polyhart &

Harold (2004), argue that what causes these fairness perceptions are attributional processes. They further argue that these attributional processes are also affected by individual and cultural differences (Polyhart & Harold, 2004).

The three-way interaction between condition, race and outcome showed statistically significant results on general procedural applicant reactions, interactional justice reaction and emotional reactions towards the hiring process. We specifically found that African American participants that are in the AI condition and who were rejected from getting a job had lower procedural justice, and negative emotional reactions compared to their White counterparts. This finding is important in that it shows that a person's demographic characteristics such as race can influence their reactions to being rejected by an AI selection system. African American participants experience more negative emotions and have lower justice perceptions when rejected by an AI, whereas the same pattern is not found with White participants. One reason could be that minorities such as African Americans have experiences that influence their perceptions of fairness such as past experiences of prejudice, discrimination, and stereotyping. To cope with these experiences of discrimination, many might employ impression management strategies to have a greater sense of control over their outcomes such as acceptance in a job application (Neel et al., 2013; Shih et al., 2013; Gioaba, & Krings, 2017). However, in AI-based selection systems, applicants may perceive less control over their outcomes because there may be fewer opportunities to appeal decisions, express opinions, or manage impressions (Gonzalez et al., 2019). This lack of opportunity for impression management may be perceived as unfair explaining the low fairness perceptions that the African American participants in this

study have. Furthermore, the AART also predicts that rejected applicants attribute their rejection to external factors (e.g., AI is unfair) compared to those who are hired, who will attribute the cause of selection to stable and internal factors, e.g., their skills (Polyhart & Harold, 2004). In addition, Brockner and Wiesenfeld (1996) also state that negative outcomes (such as rejection) prompt an information search. This makes individuals more receptive to external cues to come to conclusions about the selection process. Therefore, African Americans who have ambivalent attitudes towards AI (view AI as both able to reduce or heighten bias), when rejected by this novel selection technology attributed this outcome to situational factors, leading them to have negative fairness perceptions. Further research should be conducted to assess individual thought processes as they react to AI based selection systems.

This is an important finding since one way to promote diversity starts with how we attract, recruit, and select applicants and ensure the application process is fair to one and all including those from minority groups; how African Americans perceive AI rejection is important to pay heed to. In the case of African American participants, they showed lower perceptions of fairness in the AI condition and when this was followed by a rejection.

Negative applicant reactions lead to outcomes such as withdrawal from the selection process, which dampens the utility of the selection system and potentially curbs potential employees from joining the company (Ryan, Sacco, McFarland & Kriska, 2000). The organization could also seem unattractive to top candidates, decrease acceptance intentions, and may increase intentions to litigate (Geenen, Proost, Dijke, Witte, Grumbkow, 2012). Candidates with negative reactions to a

company's selection system may also dissuade other potential employees from applying to the company (Hausknecht, Day & Thomas, 2004). Since managing a positive image is important for an organization during the selection process, the findings can assist HR managers in weighing the advantages and disadvantages of using computer-mediated selection systems versus traditional selection procedures. In addition, findings of this study showed that minority status brings to the forefront issues that are relevant for companies and as such work on developing selection systems that can lessen this fairness perception gap amongst the races.

To add to this, the exploratory qualitative research showed that participants overwhelmingly chose to be evaluated by HR rather than AI systems. They cited the need for communication and ability to sway and exert influence on the hiring process as major reasons for their choice of HR. The theme of communication which had numerous comments from participants on being able to influence and sway the decision-making process hints at the need for impression management. While everyone has this need, African American participants had lower perceptions of fairness because of this particular chance to impression manage (see RBIM).

AI's perceived ability to lessen bias and discrimination was given as a reason for people's choice of AI. Even though there were some who said that AI can be as biased as HR depending on how it was coded, the reasons for people's choice of AI was this perceived lack of bias. Therefore, organizations should understand the pros and cons of each medium for hiring purposes.

Chapter 6: Contributions and Limitations of the Study

This study used Mturk HIT job application which allowed for greater external validity and generalizability. This study bridged the methodological gap in the previous experimental vignette studies done in this topic area (Gonzalez et al., 2019). However, more field studies with different types of job applicants can help us further understand applicant reactions to AI evaluations.

Theoretical Implications

This study also offers important theoretical and practical implications. First, it fills a literature gap in the applicant reactions to AI selection processes (e.g., Langer et al., 2017). The findings from this research, support past studies suggesting applicants favor HR more (Langer et al., 2017, Gonzalez et al., 2019) and also extend beyond this past work in important ways. First, AI was not only associated with more negative interactional justice perceptions but also more negative perceptions of some facets of procedural justice. Although past work did not find a negative effect of AI evaluations on procedural justice (Gonzalez at al., 2019), the current study had participants undergo what they believed to be an actual assessment with a tangible outcome, suggesting that procedural justice is affected by use of AI in selection.

Second, findings showed that many of the relationships between AI (vs. HR) and justice outcomes occurred when the outcome was rejection. This suggests that rejection in particular acts like a fairness heuristic when the selection tool is novel (such is AI) and when the decision is high stakes (being hired). The attribution of blame is assigned to the AI when the outcome is rejection, which acts like a fairness heuristic. The fairness-heuristic theory recognizes that outcomes do play a role in

affecting procedural justice judgments. This is particularly true when trust is missing (Van den Bos, Wilke, & Lind, 1998) or when there is a lack of social comparison information (Van den Bos et al., 1997), or when domain knowledge is perceived to be lacking (See, 2009). Thus, when these elements are lacking, people rely more on outcomes to arrive at overall impressions of fairness.

Finally, this study also showed that Applicant reactions theory should broaden its literature to include applicant characteristics such as race. Here, race-based identity management theory (Roberts et.al., 2008) was used to explore some of the hypothesis. While they apply their theory within a work context where racial minorities are interacting with their co-workers to mold how they are viewed, the author of this paper attempted to apply it to the job application process. The theory asserts that perceptions that one's group is stigmatized, general impression management tendencies and centrality of identity (its importance to the person) are likely to affect how racial minorities interact with their colleagues in the workplace by affecting how they present themselves (claim or downplay it). This study found that African Americans have more negative reactions when evaluated by an AI and when the outcome is rejection. This interaction was proposed to be due to two major factors. For one, African American applicants may desire to impression manage more than White applicants because of past experiences of discrimination that colors how they intend to impression manage and in turn affect the outcome.

Procedures enhance perceptions of inclusion by allowing one to voice or get access to decision makers. These feelings of inclusion/exclusion lead the person to be more accepting or rejecting of the outcomes received from the authority (Bos, Lind &

Wilke, 2001). Several laboratory studies show that participants rely more upon procedural information such as having the opportunity to voice as a kind of heuristic when forming outcome fairness judgments when social comparisons are not available (Van den Bos, Wilke, Lind, & Vermunt, 1998). That is, participants reactions are affected by procedural fairness information (such as opportunity to voice) when they do not know whether the authority who is doing the selection could be trusted. AI is perceived as having to lack this mechanism to interact and impression manage (to voice). Furthermore, the fairness heuristic theory states that social interdependence and socially based identity processes are important markers to form fairness heuristics (Bos, Lind & Wilke, 2001). In fact, if people have a clearer idea about the trustworthiness of the authority, procedural justice dimensions matter less, and participants resolve to forming heuristics based on authority. This is what Lind (1995) referred to as the fundamental social dilemma, where ceding authority to another entity may lead to exclusion and exploitation. For this reason, people look to the fairness of these authority figures to assess their standing. Therefore, whether or not an authority can be trusted affects one's fairness heuristics/judgments. African Americans may be warier and more skeptical of such authorities due to past experiences of discrimination. AI due to its novelty and the lack of a two-way interaction, may produce more mistrust among African Americans.

The other reason would probably have to do with applicant attribution theory (Polyhart & Harold, 2004), where negative outcomes such as rejection are externalized while acceptance is internalized as one's own effort or skill. Unlike Gilliland's (1993) model AART proposes that applicant attributions with respect to

locus, stability, and controllability directly influence applicant perceptions, including perceptions of fairness. The perceived lack of control in AI evaluations is another probable reason why participants (especially African Americans) perceived AI as less fair since they have had past experiences of past discrimination that motivate them to exert more control in selection.

I suggest that this three-way interaction between a person's race, AI as an evaluation medium and rejection outcome should be tested further by other studies. If similar findings hold and are further corroborated, that would suggest that applicant reactions theory needs to further incorporate person-characteristics, fairness heuristics and applicant attributions.

Practical Implications

Practically, this study shows that the interaction of race, condition and outcome affects applicants' fairness reactions. It showed that there is a reliance on fairness heuristics among individuals towards AI evaluations. But the qualitative phase of this study also demonstrated that there is an ambivalence towards AI that organizations can redirect. AI is not necessarily viewed as free from bias by the laity with some even outright stating that bias could be coded into AI systems. Certain comments from this study showed that people do not have a strong preference for either one and many have claimed that their choice depends on numerous factors, most importantly the outcome o rejection. Some have commented that the use of both AI and HR during the selection process would be more favorable to erase the cons of either route. While more participants chose to be evaluated by HR, people may react more favorably to AI/ML if used together with HR. Gonzalez et al., 2019, found that

human involvement mitigated the negative reactions that people have towards AI based systems. While this study did not directly test for that, certain comments and ambivalent comments hint that the use of both systems may be complementary and be perceived better. Furthermore, Burton, Stein, and Jensen's (2019) suggest that a mix of a human-algorithm decision would outperform a single system decision. They suggest that this mix of human and AI decision making would mitigate mistrust and aversions to AI.

Gonzalez at al., (2019) suggests that humans could be involved throughout the AI based selection process such as by emphasizing that humans' decision makers were involved during the training of the algorithms and reviewing process. He further suggests that communication that human resources was used in tandem with an AI system by the hiring organization would be especially important in industries where applicants are not as familiar with AI/ML systems.

Connected to the above theory as to why AI is perceived as less fair, is the use of explanations can lessen these negative fairness perceptions. (Greenberg, 1990). Explanations for why a procedure is being used, why AI is being used and criteria it's looking for could help. This is related to informational justice where explanations are given regarding selection processes (Shapiro, Buttner, & Barry, 1994).

Ployhart et al. (2005) suggests that applicant reactions are affected by explanations. This is because explanations provide information that help guide applicants' attributional analysis, thus how they form their fairness perceptions. For example, applicants who receive no explanations or receive diversity explanations (to increase workforce diversity) are more likely to attribute the causes to external factors

such as the AI being faulty, unfair procedures, preferential treatment etc. When accurate reasons and explanations are given illuminating the validity and fairness of the tool (AI for example), internal and stable characteristics such as effort and skill will be utilized (Schroth et al., 2000). There is evidence that a timely, procedure relation information could lend itself to more positive fairness heuristics (Truxillo, Bauer, Campion, & Paronto, 2002). A study has shown that supplying applicants with information regarding how AI collects and uses data increased favorable perceptions (Langer et al., 2018).

Furthermore, explanations for the selection decision itself should also be available. Studies have shown that it can mitigate negative fairness perceptions (Ployhart et al., 1999). The effect of explanations to AI decision making have been inconclusive, but the authors did find that the use of multiple explanation styles attenuated some of the negative perceptions that applicants had (Binns et al.,2018).

In conclusion, this study fills an important gap by providing evidence that the use of AI in selection is viewed unfavorably and that there is an interaction between one's race, AI evaluation and being rejected by an AI. Organizations thus need to carefully weigh the pros and cons of using AI and come up with ways to mitigate some of these negative perceptions (such as using mixed systems and using explanations). We suggest that further studies that extend this work should be carried out.

Appendices

Appendix A: Mturk Design

Prior to beginning this study, I designed pre-screen/pre-qualification questions that are usually found in job applications to complete a fake HIT (a Human Intelligence Task, or what MTurk calls its self-contained tasks). This is where the deception occurs because there is no task they must do after this "prequalification". In these series of questions, I asked about gender, age, racial identification and other demographic questions. These participants will be paid $1.00 for the first phase and $1.00 for the second survey phase.

HIT: Data Cleaning: Pre-qualification needed.

(1) Clean excel data of medical providers, including:

- Check that first name and last name are filled out, and accurate when compared against their website

- Check if a provider is an independent medical practice or part of a group practice, and categorize their status accordingly

(2) Assess the medical provider's specialties by looking at their websites

Job Application/pre-qualification Questions:

These pre-qualification questions will allow you to participate in our data cleaning HIT. Proceed with the job application questions:

1. How many years of work experience do you have? (Part-time work counts)_____

2. How would you rate your job performance in the job you currently hold relative to others who are performing the same job? (MTurk only)

I could use improvement

I am a satisfactory performer

I am a top performer

3. How quickly do you learn new tasks or assignments relative to other employees? (MTurk only)

It takes me a little longer than most employees

I learn at the same pace as most other employees

I learn more quickly than most other employees

4. Could you briefly describe a time you dealt with high stress for a task that had to be done for a job? _____

5. Could you briefly describe a time where you had/lacked attention to detail? _____

7. How would you describe yourself? _____

This was followed by the questions/job application written above (The Job Application)

Condition HR:

In progress message: Your application is now being reviewed by a human resources manager and results will be made in a couple of minutes. Please remain in the portal. *Acceptance:* Your application was reviewed by a human resources manager. We would like to inform you that you have been accepted to complete the HIT job you have applied for. Before proceeding with the task, there are surveys to be filled about the job application process. Please press next to continue.
Rejection: Your application was reviewed by a human resources manager. We regret to inform you that you have been rejected to complete the HIT job you have applied for. However, you will be paid X for completing the surveys about the job application and how you felt about it. Please press next to continue.

Condition AI:

In progress message: Your application is now being reviewed by an Artificial Intelligence System and results will be made in a couple of minutes. Please remain in the portal. Acceptance: Your application was reviewed by an Artificial Intelligence tool. We would like to inform you that you have been accepted to complete the HIT job you have applied for. Before proceeding with the task, there are surveys to be filled about the job application process. Please press next to continue.
Rejection: Your application was reviewed by an Artificial Intelligence tool. We regret to inform you that you have been rejected to complete the HIT job you have applied for. However, you will be paid X for completing the surveys about the job application. Please press next to continue.

Items used:

Appendix B: Fairness Reactions

Procedural Justice

Strongly disagree=1, Disagree=2, Neither agree nor disagree=3, Agree=4, Strongly agree=5

Job-Relatedness-Predictive

-Doing well on this test means a person can do the HIT job well.

-A person who scored well on this test will be a good Data Cleaning technician.

Information Known

-I understood in advance what the testing processes would be like.

-I knew what to expect on the test.

-I had ample information about what the format of the test would be.

Chance to Perform

-I could really show my skills and abilities through this test.

-This test allowed me to show what my job skills are.

-This test gives applicants the opportunity to show what they can really do.

-I was able to show what I can do on this test.

Reconsideration Opportunity

-I was given ample opportunity to have my test results rechecked, if necessary.

-There was a chance to discuss my test results with someone

-I feel satisfied with the process for reviewing my test results

-Applicants were able to have their test results reviewed if they wanted

-The opportunities for reviewing my test results were adequate.

Feedback

-I had a clear understanding of when I would get my test results.

-I knew when I would receive feedback about my test results.

-I was satisfied with the amount of time it took to get feedback on my test results.

Interactional Justice

"I think I am treated fairly in the decision process via the decisions made by [AIvs HR]."

"I am treated with dignity by the organization that appointed [AIvs HR] to make employment decisions."

"I am treated with respect by the organization that appointed [AIvs HR] to make employment decisions."

General Reaction Items

"I trust the factors used by a [AI vs HR] to make the employment decision"

"I worry about a lack of communication during the application process"

"I am concerned that my privacy might be invaded during the process"

"The decision made by [AIvs HR] is consistent and predictable."

"The decision made by [AIvs HR] is free of bias."

"The decision made by [AIvs HR] is based on accurate information."

“I feel that the decision made by [AIvs HR] provides an accurate assessment of my skills and abilities.”

“[AIvs HRt] would definitely pick the right person for the job.”

“By having [AIvs HR] make employment decisions, applicants would have the opportunity to show what they can really do on the job.”

Appendix C: Emotional Responsiveness:

How much do you agree or disagree that the hiring process made you feel?

	Strongly agree	Agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Disagree	Strongly disagree
Happy							
Joyful							
Proud							
Disappointed							
Angry							
Frustrated							

Appendix E: Familiarity with AI

“How much experience do you have with using artificial intelligence?”

“How knowledgeable are you about artificial intelligence?”

Appendix F: Demographic Questionnaire

1. What is your age (in years)? _____

2. What is your gender?

Male

Female

Other_____

Do you identify as transgender?

Yes

No

3. Please select your race below (may select more than one):

American Indian or Alaska Native

Asian

Black or African American

Native Hawaiian or Other Pacific Islander

White

Other

Appendix G: Probing Qualitative Questions:

1.“If you had to choose, would you rather have a hiring decision made about you by an AI algorithm or by a recruiter/hiring manager (i.e., a human decision-maker)? Please tell us the reason for your choice.

2. “What factors contribute to your level of discomfort/comfort with the use of AI in hiring Decisions?”

Debriefing Script:

Thank you for your participation in the study. I would like to take a few minutes to tell you about the purpose of this study. The goal of this study is to look at how people respond to job offers and rejection made by Artificial intelligence in comparison to those made by Human resources personnel. Specifically, we are

interested if job applicants see decisions made by AI systems as fair. We also looked if race, age, and familiarity with artificial intelligence systems affect applicants' reactions to AI-powered job applications.

This means that there is no HIT job waiting to be done, your participation in this study is the HIT. We adopted this approach so that participants would feel that there are high stakes to be accepted for the job. Furthermore, our purpose was not to "trick" you, but to allow you to respond naturally to the prequalification/job application and to the decisions given by a human versus by an AI. So, as you may see there are some misleading aspects to this study, but we hope that you understand that they were included for an important reason. We believe this study is important because it allows us to better understand how applicants feel about being denied or offered a job by an AI.

All of the information that was collected today will be kept in complete confidentiality. We are not interested in any one participant's responses by themselves. Rather, we are interested in the general responses of all participants when they are combined together.

Bibliography

Anderson, B., & Horn, R. (2012). Community colleges in the information age: Gains associated with students' use of computer technology. Journal of Educational Computing Research, 47, 51-65. doi:10.2190/EC.47.1.c

Anderson, M. (2017). Digital divide persists even as lower-income Americans make gains in tech adoption. Washington, DC: Pew Research Center.

Anderson, N. (2003). Applicant and recruiter reactions to new technology in selection: A critical review and agenda for future research. International Journal of Selection and Assessment, 11(2--- 3), 121-136.

Arvey, R. D., & Sackett, P. R. (1993). Fairness in selection: Current developments and perspectives. In Personnel selection. Jossey-Bass.

Basch, J. M., & Melchers, K. G. (2019). Fair and Flexible?! Explanations can improve applicant reactions toward asynchronous video interviews. Personnel Assessment and Decisions, 5(3), 2.

Bauer, T. N., Maertz Jr, C. P., Dolen, M. R., & Campion, M. A. (1998). Longitudinal assessment of applicant reactions to employment testing and test outcome feedback. Journal of applied Psychology, 83(6), 892.

Bauer, T. N., Maertz Jr, C. P., Dolen, M. R., & Campion, M. A. (1998). Longitudinal assessment of applicant reactions to employment testing and test outcome feedback. Journal of applied Psychology, 83(6), 892.

Bauer, T. N., Truxillo, D. M., Paronto, M. E., Weekley, J. A., & Campion, M. A. (2004). Applicant reactions to different selection technology: Face-to-Face, interactive voice response, and computer-assisted telephone screening interviews. International Journal of Selection and Assessment, 12, 135e148. https://doi.org/10. 1111/j.0965-075x.2004.00269.x.

Bauer, T. N., Truxillo, D. M., Sanchez, R. J., Craig, J. M., Ferrara, P., & Campion, M. A. (2001). Applicant reactions to selection: Development of the selection.

Bauer, T. N., Truxillo, D. M., Sanchez, R. J., Craig, J. M., Ferrara, P., & Campion, M. A. (2001). Applicant reactions to selection: Development of the selection procedural justice scale (SPJS). Personnel Psychology, 54(2), 388–420. https://doi.org/10.1111/j.1744-6570.2001.tb00097.x

Bauer, T. N., Truxillo, D. M., Tucker, J. S., Weathers, V., Bertolino, M., Erdogan, B., & Campion, M. A. (2006). Selection in the information age: The impact of privacy concerns and computer experience on applicant reactions. Journal of Management, 32(5), 601-621.

Behrend, T. S., & Landers, R. N. (2019). Introduction to the Special Issue on Advanced Technologies in Assessment: A Science-Practice Concern. Personnel Assessment and Decisions, 5(3), 1.

Bertolino, M., & Steiner, D. D. (2007). Fairness reactions to selection methods: An Italian study. International Journal of Selection and Assessment, 15(2), 197-205.

Bies, R. J., & Shapiro, D. L. (1988). Voice and justification: Their influence on procedural fairness judgments. Academy of management journal, 31(3), 676-685.

Bigman, Y. E., & Gray, K. (2018). People are averse to machines making moral decisions. Cognition, 181, 21-34.

Binns, R., Van Kleek, M., Veale, M., Lyngs, U., Zhao, J., & Shadbolt, N. (2018, April). 'It's Reducing a Human Being to a Percentage' Perceptions of Justice in Algorithmic Decisions. In Proceedings of the 2018 Chi conference on human factors in computing systems (pp. 1-14).

Blacksmith, N., Wilford, J. C., & Behrend, T. S. (2016). Technology in the employment interview: A meta-analysis and future research agenda. Personnel Assessment and Decisions, 2, 12-20. doi:10.25035/pad.2016.002

Bondarouk, T., & Brewster, C. (2016). Conceptualising the future of HRM and technology research. The International Journal of Human Resource Management, 27(21), 2652-2671.

Bos, V. D. K., Lind, E. A., & Wilke, H. A. (2001). The psychology of procedural and distributive justice viewed from the perspective of fairness heuristic theory.

Brenner, F., Ortner, T. M., & Fay, D. (2016). Asynchronous video interviewing as a new technology in personnel selection: The applicant's point of view. Frontiers in Psychology, 7:863, 1-11. doi:10.3389/fpsyg.2016.00863

Brockner, J., & Wiesenfeld, B. M. (1996). An integrative framework for explaining reactions to decisions: interactive effects of outcomes and procedures. Psychological bulletin, 120(2), 189.
Brockner, J., & Wiesenfeld, B. M. (1996). An integrative framework for explaining reactions to decisions: interactive effects of outcomes and procedures. Psychological bulletin, 120(2), 189.

Caliskan, A., Bryson, J. J., & Narayanan, A. (2017). Semantics derived automatically from language corpora contain human-like biases. Science, 356(6334), 183-186.

Campion, M. C., Campion, M. A., Campion, E. D., & Reider, M. H. (2016). Initial investigation into computer scoring of candidate essays for personnel selection. Journal of Applied Psychology, 101(7), 958.

Chalfin, A., Danieli, O., Hillis, A., Jelveh, Z., Luca, M., Ludwig, J., & Mullainathan, S. (2016). Productivity and selection of human capital with machine learning. American Economic Review, 106(5), 124-27.

Chapman, D. S., Uggerslev, K. L., & Webster, J. (2003). Applicant reactions to face-to-face and technology-mediated interviews: A field investigation. Journal of Applied Psychology, 88(5), 944.

Cheung, M. F. (2013). The mediating role of perceived organizational support in the effects of interpersonal and informational justice on organizational citizenship behaviors. Leadership & Organization Development Journal.

Cole, J. I., Suman, M., Schramm, P., van Bel, D., Lunn, B., Maguire, P., ... & Aquino, J. S. (2000). The UCLA Internet report: Surveying the digital future. Los Angeles: UCLA.[online] Available at: http://ccp. ucla. edu/UCLA-Internet-Report-2000. pdf (18 October 2004).

Colquitt, J. A., & Zipay, K. P. (2015). Justice, fairness, and employee reactions. Annu. Rev. Organ. Psychol. Organ. Behav., 2(1), 75-99.

Cropanzano, R., & Schminke, M. (2001). Using social justice to build effective work groups. Groups at work: Theory and research, 143-171.

De Groot, T., & Gooty, J. (2009). Can nonverbal cues be used to make meaningful personality attributions in employment interviews? Journal of Business and Psychology, 24(2), 179–192. https://doi.org/10.1007/s10869-009-9098-0

Dineen, B. R., Noe, R. A., & Wang, C. (2004). Perceived fairness of web-based applicant screening procedures: Weighing the rules of justice and the role of individual differences. Human Resource Management: Published in Cooperation with the School of Business Administration, The University of Michigan and in alliance with the Society of Human Resources Management, 43(2-3), 127-145.

Ensher, E. A., Nielson, T. R., & Grant-Vallone, E. (2002). Tales from the hiring line: effects of the internet and technology on HR processes. Organizational dynamics, 31(3), 224-244.

Feldman, D. C., & Klich, N. R. (1991). Impression management and career strategies. In R. A. Giacalone & P. Rosenfeld (Eds.), Applied Impression Management: How Image-making Affects Managerial Decisions (pp. 67–80). Newbury Park, California: Sage Publications.

Fiske, S. T. (1998). Stereotyping, prejudice, and discrimination. In D. T. Gilbert, S. T. Fiske, & G. Lindzey (Eds.), The handbook of social psychology (4th ed., Vol. 2, pp. 357–411). Boston: McGraw-Hill

Flint, D. H., & Haley, L. M. (2013). Distributive justice in human resources management: A multisystem approach. The Journal of American Business Review, Cambridge, 2(1), 50-57.

Folger, R., & Cropanzano, R. (2001). Fairness theory: Justice as accountability. Advances in organizational justice, 1(1-55), 12.

Folger, R., & Cropanzano, R. (2001). Fairness theory: Justice as accountability. In J.

Gardner, S. D., Lepak, D. P., & Bartol, K. M. (2003). Virtual HR: The impact of information technology on the human resource professional. Journal of Vocational Behavior, 63(2), 159-179.

Gardner, S. D., Lepak, D. P., & Bartol, K. M. (2003). Virtual HR: The impact of information technology on the human resource professionals. Journal of Vocational Behavior, 63(2), 159-179.

Gardner, W. L. III. (1992). Lessons in organizational dramaturgy: The art of impression management. Organizational Dynamics, 21(1), 33–46.

Gardner, W. L., & Martinko, M. J. (1988). Impression management in organizations. Journal of Management, 14(2), 321–338

Geenen, B., Proost, K., Van Dijke, M., De Witte, K., & Von Grumbkow, J. (2012). The role of affect in the relationship between distributive justice expectations and applicants' recommendation and litigation intentions. International Journal of Selection and Assessment, 20(4), 404-413.

Geenen, B., Proost, K., Van Dijke, M., De Witte, K., & Von Grumbkow, J. (2012). The role of affect in the relationship between distributive justice expectations and applicants' recommendation and litigation intentions. International Journal of Selection and Assessment, 20(4), 404-413.

Gilliland, S. W. (1993). The perceived fairness of selection systems: An organizational justice perspective. Academy of management review, 18(4), 694-734.

Gilmore, D. C., & Ferris, G. R. (1989). The effects of applicant impression management tactics on interviewer judgments. Journal of Management, 15(4), 557-564.

Gilmore, D. C., & Ferris, G. R. (1989). The effects of applicant impression management tactics on interviewer judgments. Journal of Management, 15(4), 557-564.

Gioaba, I., & Krings, F. (2017). Impression management in the job interview: An effective way of mitigating discrimination against older applicants? Frontiers in Psychology, 8, 770.

Goldman, B., & Cropanzano, R. (2015). “Justice” and “fairness” are not the same thing. Journal of Organizational Behavior, 36(2), 313-318.

Gonzalez, M. F., Capman, J. F., Oswald, F. L., Theys, E. R., & Tomczak, D. L. (2019). “Where’s the IO?” Artificial Intelligence And Machine Learning in Talent Management Systems. Personnel Assessment and Decisions, 5(3), 5.

Gorman, C. A., Robinson, J., & Gamble, J. S. (2018). An investigation into the validity of asynchronous web-based video employment-interview ratings. Consulting Psychology Journal: Practice and Research, 70(2), 129.

Gray, H. M., Gray, K., & Wegner, D. M. (2007). Dimensions of mind perception. science, 315(5812), 619-619.

Greenberg, J., & Cropanzano, R. (2001). (Ed.). Advances in organizational justice. Stanford, CA: Stanford University Press

Guchait, P., Ruetzler, T., Taylor, J., & Toldi, N. (2014). Video interviewing: A potential selection tool for hospitality managers–A study to understand applicant perspective. International Journal of Hospitality Management, 36, 90-100.

Hall, J. & Stevens, P. (1991). Rigor in feminist research. Advances in Nursing Science, 13(3), 16-29

Handler, C.A., & Hunt, S.T. (2003). Rocket-hire buyer's guide to web-based screening & staffing assessment systems. United States: Rocket-Hire

Hausknecht, J. P., Day, D. V., & Thomas, S. C. (2004). Applicant reactions to selection procedures: An updated model and meta-analysis. Personnel psychology, 57(3), 639-683.

Helms, J. E. (1990). Black and white racial identity: Theory, research and practice. New York, NY: Greenwood.

Highhouse, S., Lievens, F., & Sinar, E. F. (2003). Measuring attraction to organizations. Educational and Psychological Measurement, 63, 986e1001. https://doi.org/ 10.1177/0013164403258403

Hoffman, M., Kahn, L. B., & Li, D. (2018). Discretion in hiring. The Quarterly Journal of Economics, 133(2), 765-800.

Hughes R and Huby M (2004) The construction and interpretation of vignettes in social research. Social Work & Social Sciences Review 11(1): 36–51.

Hunthausen JM. (2000). Predictors of task and contextual performance: Frame-ofreference effects and applicant reaction effects on selection system validity. Unpublished doctoral dissertation. Portland State University.

Illingworth, A. J. (2015). Big data in IO psychology: Privacy considerations and discriminatory algorithms. Industrial and Organizational Psychology, 8(4), 567.

Jellison, J. M. (1981). Reconsidering the attitude concept: A behavioristic self-presentation forumulation. In J. T. Tedeschi (Ed.), Impression Management Theory and Social Psychological Research (pp. 104–126). New York: Academic Press.

Johnson, D. G., & Verdicchio, M. (2017). Reframing AI discourse. Minds and Machines, 27(4), 575-590.

Konradt, U., Warszta, T., & Ellwart, T. (2013). Fairness perceptions in web-based selection: Impact on applicants' pursuit intentions, recommendation intentions, and intentions to reapply. International Journal of Selection and Assessment, 21(2), 155-169.

Kühl, N., Goutier, M., Hirt, R., & Satzger, G. (2019, January). Machine learning in artificial intelligence: Towards a common understanding. In Proceedings of the 52nd Hawaii International Conference on System Sciences.

Kühl, N., Goutier, M., Hirt, R., & Satzger, G. (2020). Machine learning in artificial intelligence: Towards a common understanding. arXiv preprint arXiv:2004.04686.

Kuncel, N. R., Klieger, D. M., Connelly, B. S., & Ones, D. S. (2013). Mechanical versus clinical data combination in selection and admissions decisions: A meta-analysis. Journal of Applied Psychology, 98(6), 1060.

Lahuis, D. M., Perreault, N. E., & Ferguson, M. W. (2003). The Effect of Legitimizing Explanations on Applicants' Perceptions of Selection

Assessment Fairness 1. Journal of Applied Social Psychology, 33(10), 2198-2215.

Langer, M., König, C. J., & Krause, K. (2017). Examining digital interviews for personnel selection: Applicant reactions and interviewer ratings. International Journal of Selection and Assessment, 25(4), 371-382.

Lee, M. K. (2018). Understanding perception of algorithmic decisions: Fairness, trust, and emotion in response to algorithmic management. Big Data & Society, 5(1), 2053951718756684.

Leventhal, G.S. (1980). What should be done with equity theory? New approaches to the study of fairness in social relationships. In K. Gergen, M. Greenberg, & R. Willis (Eds.), Social exchange: Advances in theory and research (pp. 27-55). New York: Plenum Press.

Lind, E. A., Kulik, C. T., Ambrose, M., & de Vera Park, M. V. (1993). Individual and corporate dispute resolution: Using procedural fairness as a decision heuristic. Administrative Science Quarterly, 224-251.

Mann, G., & O'Neil, C. (2016). Hiring algorithms are not neutral. Harvard Business Review, 9.

Marler, J. H., & Fisher, S. L. (2013). An evidence-based review of e-HRM and strategic human resource management. Human resource management review, 23(1), 18-36.

Mayer, D. M., & Ployhart, R. E. (2007). Explaining away injustice: When, why, and for whom are explanations most effective. Working paper.

McCarthy, J. M., Bauer, T. N., Truxillo, D. M., Anderson, N. R., Costa, A. C., & Ahmed, S. M. (2017). Applicant perspectives during selection: A review addressing "So what?,""What's new?," and "Where to next?". Journal of Management, 43(6), 1693-1725.

McManus, M. A., & Ferguson, M. W. (2003). Biodata, personality, and demographic differences of recruits from three sources. International Journal of Selection and Assessment, 11(2-3), 175-183.

McNall, L. A., & Roch, S. G. (2007). Effects of Electronic Monitoring Types on Perceptions of Procedural Justice, Interpersonal Justice, and Privacy 1. Journal of Applied Social Psychology, 37(3), 658-682.

Mor Barak, M. E., Lizano, E. L., Kim, A., Duan, L., Rhee, M. K., Hsiao, H. Y., & Brimhall, K. C. (2016). The promise of diversity management for climate of inclusion: A state-of-the-art review and meta-analysis. Human Service Organizations: Management, Leadership & Governance, 40(4), 305-333.

Mor Barak, M.E. 2015. Inclusion is the Key to Diversity Management, but What is Inclusion?", (Guest Editorial) Human Service Organizations: Management Leadership and

Nagtegaal, R. (2021). The impact of using algorithms for managerial decisions on public employees' procedural justice. Government Information Quarterly, 38(1), 101536.

Neel, R., Neufeld, S. L., & Neuberg, S. L. (2013). Would an obese person whistle Vivaldi? Targets of prejudice self-present to minimize appearance of specific threats. Psychological Science, 24(5), 678-687.

Ng, E. S., & Sears, G. J. (2012). CEO leadership styles and the implementation of organizational diversity practices: Moderating effects of social values and age. Journal of business ethics, 105(1), 41-52.

Nikolaou, I., & Judge, T. A. (2007). Fairness reactions to personnel selection techniques in Greece: The role of core self-evaluations. International Journal of Selection and Assessment, 15(2), 206-219.

Pallant, J. (2001). SPSS survival manual. Maidenhead.

Pan, X., Chen, M., Hao, Z., & Bi, W. (2018). The effects of organizational justice on positive organizational behavior: Evidence from a large-sample survey and a situational experiment. Frontiers in psychology, 8, 2315.

Ployhart, R. E., & Ryan, A. M. (1998). Applicants' reactions to the fairness of selection procedures: The effects of positive rule violations and time of measurement. Journal of Applied Psychology, 83(1), 3–16. https://doi.org/10.1037/0021-9010.83.1.3

Ployhart, R. E., & Schneider, B. (2017). Multilevel selection and prediction: Theories, methods, and models. The Blackwell Handbook of Personnel Selection, 495-516.

Ployhart, R. E., Ryan, A. M., & Bennett, M. (1999). Explanations for selection decisions: Applicants' reactions to informational and sensitivity features of explanations. Journal of applied Psychology, 84(1), 87.

Potosky, D., & Bobko, P. (2004). Selection testing via the internet: Practical considerations and exploratory empirical findings. Personnel Psychology, 57(4), 1003-1034.

Potosky, D., & Bobko, P. (2004). Selection testing via the internet: Practical considerations and exploratory empirical findings. Personnel Psychology, 57(4), 1003-1034. 2(2), 171.

Prahl, A., & Van Swol, L. (2017). Understanding algorithm aversion: When is advice from automation discounted?. Journal of Forecasting, 36(6), 691-702.

Roberts, L. M., Cha, S. E., & Kim, S. S. (2014). Strategies for managing impressions of racial identity in the workplace. Cultural Diversity and Ethnic Minority Psychology, 20(4), 529.

Roberts, L. M., Settles, I. H., & Jellison, W. A. (2008). Predicting the strategic identity management of gender and race. Identity: An International Journal of Theory and Research, 8(4), 269-306.

Russell, D. P. (2007). Recruiting and staffing in the electronic age: A research-based perspective. Consulting Psychology Journal: Practice and Research, 59, 91-101. doi:10.1037/1065-9293.59.2.91

Ryan A. M, Sacco JM, McFarland LA, Kriska SD. (2000). Applicant self-selection: Correlates of withdrawal from a multiple hurdle process. Journal of Applied Psychology, 85, 163–179

Ryan, A. M., & Chan, D. (1999). Perceptions of the EPPP: How do licensure candidates view the process?. Professional Psychology: Research and Practice, 30(5), 519.

Ryan, A. M., & Ployhart, R. E. (2000). Applicants' Perceptions of Selection Procedures and Decisions: A Critical Review and Agenda for the Future. Journal of Management, 26(3), 565–606. https://doi.org/10.1177/014920630002600308

Ryan, A. M., & Ployhart, R. E. (2000). Applicants' perceptions of selection procedures and decisions: A critical review and agenda for the future. Journal of management, 26(3), 565-606.

Ryan, A. M., Sacco, J. M., McFarland, L. A., & Kriska, S. D. (2000). Applicant self-selection: Correlates of withdrawal from a multiple hurdle process. Journal of applied psychology, 85(2), 163.

Scarborough, W. J., Lambouths III, D. L., & Holbrook, A. L. (2019). Support of workplace diversity policies: The role of race, gender, and beliefs about inequality. Social science research, 79, 194-210.

Schinkel, S., Vianen, A., & Dierendonck, D. (2013). Selection fairness and outcomes: A field study of interactive effects on applicant reactions. International Journal of Selection and Assessment, 21(1), 22-31.

Schleicher, D. J., Venkataramani, V., Morgeson, F. P., & Campion, M. A. (2006). So you didn't get the job… now what do you think? Examining opportunity-to-perform fairness perceptions. Personnel Psychology, 59(3), 559-590.

Schmit MJ, Ryan A. M. (1997). Applicant withdrawal: The role of test-taking attitudes and racial differences. PERSONNEL PSYCHOLOGY, 50, 855–876.

Schmitt, N., & Coyle, B. W. (1976). Applicant decisions in the employment interview. Journal of Applied Psychology, 61(2), 184.

See, K. E. (2009). Reactions to decisions with uncertain consequences: Reliance on perceived fairness versus predicted outcomes depends on knowledge. Journal of personality and social psychology, 96(1), 104.

Shapiro, D. L., Buttner, E. H., & Barry, B. (1994). Explanations: What factors enhance their perceived adequacy?. Organizational behavior and human decision processes, 58(3), 346-368.

Shih, M., Young, M. J., & Bucher, A. (2013). Working to reduce the effects of discrimination: Identity management strategies in organizations. American Psychologist, 68(3), 145.

Society for Industrial, Organizational Psychology (US), & American Psychological Association. Division of Industrial-Organizational Psychology. (2003). Principles for the validation and use of personnel selection procedures. The Society.

Stephan, M., Brown, D., & Erickson, R. (2017). Talent acquisition: Enter the cognitive recruiter. Haettu, 5, 2018.

Stone, D. L., Deadrick, D. L., Lukaszewski, K. M., & Johnson, R. (2015). The influence of technology on the future of human resource management. Human Resource Management Review, 25(2), 216-231.

Stone, D. L., Lukaszewski, K. M., Stone-Romero, E. F., & Johnson, T. L. (2013). Factors affecting the effectiveness and acceptance of electronic selection systems. Human Resource Management Review, 23, 50-70.

Straus, S. G., Miles, J. A., & Levesque, L. L. (2001). The effects of video conference, telephone, and face-to-face media on interviewer and applicant judgments in employment interviews. Journal of management, 27(3), 363-381.

Swearingen, K., & Sinha, R. (2001, September). Beyond algorithms: An HCI perspective on recommender systems. In ACM SIGIR 2001 workshop on recommender systems (Vol. 13, No. 5-6, pp. 1-11).

Taylor, M. S., & Bergmann, T. J. (1987). Organizational recruitment activities and applicants' reactions at different stages of the recruitment process. Personnel Psychology, 40(2), 261–285. https://doi.org/10.1111/j.1744-6570.1987.tb00604.x

Taylor, M. S., & Sniezek, J. A. (1984). The college recruitment interview: Topical content and applicant reactions. Journal of Occupational Psychology, 57(2), 157–168. https://doi.org/10.1111/j.2044-8325.1984.tb00157.x

Thibaut, J. W., & Walker, L. (1975). Procedural justice: A psychological analysis. L. Erlbaum Associates.

Truxillo, D. M., & Bauer, T. N. (2011). Applicant reactions to organizations and selection systems.

Truxillo, D. M., & Bauer, T. N. (2011). Perceived fairness of hiring practices. In S. Zedeck (Ed.), Vol. 2. APA handbook of industrial and organizational psychology: Selecting and developing members for the organization. Washington, DC: American Psychological Association.

Van den Bos, K., Lind, E. A., Vermunt, R., & Wilke, H. A. (1997). How do I judge my outcome when I do not know the outcome of others? The psychology of the fair process effect. Journal of personality and social psychology, 72(5), 1034.

Van den Bos, K., Wilke, H. A., & Lind, E. A. (1998). When do we need procedural fairness? The role of trust in authority. Journal of Personality and social Psychology, 75(6), 1449.

Van Esch, P., Black, J. S., & Ferolie, J. (2019). Marketing AI recruitment: The next phase in job application and selection. Computers in Human Behavior, 90, 215-222.

Wallace, P., & Clariana, R. B. (2005). Gender differences in computer-administered versus paper-based tests. International Journal of Instructional Media, 3

Waung, M., & Brice, T. S. (2000). Communicating negative hire decisions to applicants: Fulfilling psychological contracts. Journal of Business and Psychology, 15(2), 247-263.

Waytz, A., & Norton, M. I. (2014). Botsourcing and outsourcing: Robot, British, Chinese, and German workers are for thinking—not feeling—jobs. Emotion, 14(2), 434.