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Abstract

The increasing use of AI decision systems in recruitment processes has created challenges, including potential resistance from job applicants. To address this issue, drawing on organizational justice theory, we identify dimensions of AI explanations in the employment context and examine their impact on job applicants' perceptions of organizational justice. We conducted an experiment to understand applicants' reactions to AI versus HR managers without explanations and examined the impact of AI explanations on organizational justice perceptions and acceptance intention. Our findings show that without explanation, AI is perceived as lower organizational just and acceptance intention compared to HR managers. Organizational justice mediates the effects between outcome/process explanations of AI on acceptance intention. However, outcome explanations have a stronger impact compared to process explanations. Our study contributes to understanding explanation structures for AI-based recruitment and offers practical implications for developing explanations that improve the perceived justice of AI recruitment systems.

Keywords: AI explanations, process explanation, outcome explanation, organizational justice, human resource managers, recruitment process

Introduction

Artificial intelligence (AI) is becoming increasingly prevalent in the recruitment process, performing a range of functions such as sourcing, screening, nurturing, scheduling, engaging, and interviewing applicants (Linkedin 2018). Haenlein and Kaplan (2019) define AI as "a system's ability to correctly interpret external data, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaptation." This technology has the potential to significantly impact both employers and job applicants. Employers attach importance to AI-based selection systems because of the potential benefits they offer in terms of time and resource savings while identifying suitable candidates for open positions. Managers are interested in understanding whether the utilization of AI can attract a larger pool of applicants and enhance their organizational reputation (Cortini et al. 2019). On the other hand, job applicants are concerned about how AI algorithms and systems are employed in the hiring process, as it can impact their chances of being selected for a job. Despite the implementation of AI by prominent companies like L'Oreal and Coca-Cola in their job recruitment processes, applicants still express reservations about AI evaluating their qualifications, having voiced concerns about fairness in AI's ability to make unbiased decisions (Leslie 2019).

Limited research exists that examines employee reactions to negative decisions delivered by human versus AI in an organizational context (Lee 2018; Leyer and Schneider 2019). While some studies have suggested no difference in feedback provided by computers or humans (Mandernach 2005), the emphasis is placed on positive messages delivered rather than negative ones. To date, the preference for AI in the recruitment process has not been thoroughly examined, particularly when applicants are not yet employees and their attitudes may differ.

In the context of addressing potential adverse consequences stemming from the utilization of AI-based resume selection systems, scholars have proposed a promising avenue for mitigation: the provision of explanations elucidating AI-generated decisions (Acikgoz et al., 2020). While the extant body of literature concerning Explainable AI (XAI) underscores the favorable outcomes linked to AI explanations, such as enhanced user acceptance, trust, interactivity, and usability, it predominantly centers on XAI frameworks designed to furnish rationales for AI decisions (Gunning, 2017). Nevertheless, a conspicuous research gap persists in the comparative analysis between AI and human agents when conveying negative messages, as well as in the investigation of the relative superiority of distinct AI explanation modalities (Costabello et al., 2019).

In order to investigate these gaps, the first objective of our study is to compare rejection decisions made by human resource (HR) managers and AI in the absence of explanations. Next, we explore the impact of providing explanations for AI's rejection decision. It remains unknown whether AI, when equipped with explanations, can compete with humans in delivering negative messages. By investigating this aspect, we can determine that AI, with proper explanations is not superior or inferior to rejection decisions made by humans. Specifically, we will compare the rejection delivered by HR managers without explanation to that of AI with the process explanations. Providing process explanations can help reduce the information asymmetry for job applicants during the resume selection process, which has been shown to improve perceived organizational justice (Langer et al. 2018). We thus expect applicants to evaluate AI's rejection decision more favorably when they are provided with such explanations, compared to the rejection delivered by HR managers without explanation. The third objective is to evaluate how different types of AI explanations affect organizational justice perceptions and acceptance intention. While previous research in XAI has underscored the importance of explanations, our study aims to compare two types of explanations: process and outcome explanations.

By achieving the three objectives identified above, this study aims to make the following contributions. Firstly, by comparing the rejection delivery by HR managers and AI, this study contributes to the literature on AI. We aim to uncover the ways in which the acceptance intention of AI can be improved through the explanation. Secondly, understanding how the perceptions of organizational justice dimensions are influenced by the process and outcome explanations in the context of AI selection can contribute to the growing literature on IS, highlighting the importance of integrating organizational justice perspectives into the evaluation of AI systems. Lastly, by comparing process explanations and outcome explanations, we aim to provide practical implications for companies to enhance fairness and transparency in their AI-based recruitment process.

Theoretical Background and Literature Review

Rejection letters have been used to deliver negative messages during processes of recruitment. Previous research has examined how factors such as delivery time and personalized information (Cortini et al. 2019) included in rejection letters impact applicants' perceptions and attitudes. However, despite these investigations, these factors have not demonstrated a substantial reduction in applicant concerns (Shapiro et al. 1994a). It is evident that the provision of explanations in rejection letters remains a critical aspect because the explanation content is more important than the delivery manner (Shapiro et al. 1994a). By delving into the concept of organizational justice, we propose and test how organizational justice perceptions mediate the relationship between the explanation of AI in the rejection letter and the applicant's acceptance intention.

Rejection Letters

The manner in which organizations handle the rejection within the recruitment process has significant implications for their reputation and future recruitment efforts (Cortini et al. 2019). Extensive research has been dedicated to understanding the impact of various factors related to rejection letters on the perceptions and experiences of applicants. One important aspect is the content of rejection letters. Research has examined whether including specific details about the requirements that applicants did not meet contributes to their understanding of the rejection (Aamodt 2015). This transparency can provide applicants with valuable feedback and insights into areas where they may need to improve. Additionally, expressing appreciation for the applicant's effort and accomplishments, even in the context of rejection, has been shown to mitigate negative organizational injustice perceptions and enhance the overall applicant experience (Barešová 2008). Personalized elements in rejection letters have also been investigated. Addressing applicants by their names rather than using generic salutations can create a sense of individual recognition and demonstrate that their application was considered on a personal level (Cortini et al. 2019). This personalization can contribute to applicants' perceptions of fairness and acceptance. However, it is important to note that the factors influencing the effectiveness of rejection letters are multifaceted. Merely addressing the applicant by name, expressing appreciation and the details about the requirement as commonly practiced in human-delivered rejection letters, may not suffice when it comes to rejection letters delivered by AI.

Explanations

Applicants often desire detailed information about why and how they did not pass the selection process and consider a lack of explanation to be unjust (Greenberg 2004). The absence of clear, rational, and detailed explanations can lead to counterfactual thinking, causing applicants to imagine alternative scenarios and possibly harbor negative feelings towards the organization (Shaw et al. 2003). Therefore, incorporating "would" and "should" reducing explanations in rejection letters can positively impact applicants' perception of organizational justice (Gilliland et al. 2001). "Would" reducing explanations inform applicants that they were less qualified than the hired applicants, thereby reducing the likelihood of questioning the outcome. In contrast, "should" reducing explanations provide details about the standard and process of the selection, demonstrating that the selection was appropriate and fair. Despite the relative maturity of research on explanations in human resources, few studies (Bobocel and Zdaniuk 2013) have examined explanation dimensions, and none have focused on the AI resume selection system used in this context. Our research aims to address this gap by investigating the effects of process explanations ("should" reducing explanation) and outcome explanations ("would" reducing explanation) on acceptance intention in the context of an AI-based resume selection system.

Organizational Justice

Gilliland (1993) identified four dimensions of organizational justice, including distributive, procedural, interpersonal, and informational justice. The design and delivery of rejection letters can affect these dimensions significantly. Distributive justice is concerned with the fairness of outcomes, while procedural justice refers to the fairness of the decision-making process. Interpersonal justice is related to how applicants are treated during the process, including the level of politeness, dignity, and respect they receive. Finally, informational justice focuses on the quality and quantity of relevant information provided, including the truthfulness and justification of decisions. Studies have examined the impact of organizational justice on various outcomes, such as feedback in learning tests (Nesbit and Burton 2006), managerial skills (Feys et al. 2011), and job applications (Gilliland et al. 2001). While this research has shed light on the role of organizational justice and participants' responses to explanations in traditional rejection settings, as far as the authors are aware, no study to date has investigated the impact of AI-delivered explanations in resume selection processes. As AI systems become more prevalent in the recruitment process, it is important to enhance the perceived fairness of these systems for rejected applicants. When the dimensions of organizational justice are addressed appropriately in rejection letters delivered by AI, applicants are more likely to perceive the process as fair and just, which can ultimately affect their attitudes toward the organization.

Hypotheses

In Figure 1, our study first aims to investigate the organizational justice perceptions of rejections that are delivered by HR managers vs. AI without explanation. Next, we develop hypotheses about applicants' perceptions of rejections delivered by HR managers vs. AI with process explanations. Finally, we compare perceptions and acceptance intentions towards rejections that are delivered by AI only, but vary in regard to outcome and process explanations.

Comparison between AI and HR in the absence of explanation

The acceptance of AI versus human decisions in the context of decision delegation is influenced by the importance of the situation and task complexity (Leyer and Schneider 2019). For instance, tasks such as resume analyses and performance evaluations are complex and require more human skills, making human decisions perceived as more acceptable than algorithmic decisions without explanation (Lee 2018). This is because people tend to recognize and trust humans more due to their perceived higher moral and emotional capabilities, while algorithms are thought to lack intuition, tacit knowledge, and subjective judgment (Reber 1989). Applicants may perceive AI as fairer and more impartial due to its ability to standardize the selection process and mitigate human biases (Claudy et al. 2022). The Computers Are Social Actors (CASA) theory, suggests that individuals tend to apply the same social rules and expectations to computers as they do to other humans (Nass et al. 1994). This theory implies that people may perceive AI as having similar social characteristics to humans, which can influence their acceptance. However, the possibility of individuals perceiving AI and humans as equivalent level of justice is low due to the prevalent phenomenon of algorithm aversion, specifically in traditional tasks that are seen to require uniquely human traits (Castelo et al. 2019). For example, people perceive HR managers as possessing more empathy than AI, which positively affects organizational justice perceptions (Pelau et al. 2021). Indeed, research has shown that people are averse to AI making 'moral' decisions, because of a lack of agency and experience (i.e., mind perception) (Bigman and Gray 2018). Therefore, we propose the following hypothesis:

H1a: In the absence of explanations, applicants will be more likely to accept a rejection letter when it is submitted by an HR manager vs. AI.

H1b: In the absence of explanations, applicants will associate greater organizational justice with a rejection letter when it is submitted by an HR manager vs. AI.

Comparison between AI with the process explanation and HR without explanation

Applicants typically have a good understanding of how HR managers identify, evaluate and select candidates, but the AI-recruitment process may be opaquer to them (Mirowska and Mesnet 2022). This response can be attributed to the substantial uncertainty engendered by AI, as the unknown inner workings of AI contribute to their unease and distrust (Biran and Cotton 2017). However, do candidates perceive rejections as fairer when they are delivered by an HR manager without explanation, or an AI with explanation? Research shows that providing clear and adequate explanations is crucial to ensure transparency and fairness in the decision-making process (Tyler and Bies 2015). Specifically, process explanations can serve as a basis for evaluating the selection criteria and help applicants understand how they were rejected. More importantly, ample research shows that HR managers can be biased and, for example, often discriminate against candidates based on age, gender, attractiveness, or ethnicity (Byrne 1971). Furthermore, people tend to perceive AI to be less biased and more impartial than human decision-makers (Claudy et al. 2022), and process explanations provided by AI can further cement people's perception of fairness. We would thus expect that providing a process explanation in AI-based decision-making will result in higher perceived organizational justice compared to HR managers without an explanation. Thus, we propose that:

H2: Applicants will perceive a rejection as less organizationally just if they receive a letter without any explanation from an HR manager, compared to when they receive a rejection letter from an AI with a process explanation.

After comparing the differences between HR and AI in terms of rejection delivery, we explore how organizational justice perceptions mediate the effect of different AI explanations on acceptance intention.

Research in traditional human resource contexts has shown that process explanations have a positive effect on acceptance intention (Gilliland et al. 2001). Prior literature (Folger and Cropanzano 2001) suggests that individuals use counterfactual thoughts to assess perceived organizational justice. For example, people make psychological comparisons with what could have happened if the procedure is untransparent (Allen et al. 2009). Therefore, a comprehensive explanation is necessary to prevent personal bias and the development of counterfactuals. When a reliable explanation is provided, job applicants can use it as a reference point to evaluate the fairness of the selection process. For instance, data source explanation helps job applicants understand the accuracy and validity of the information used in the selection process (Albornoz et al. 2012). The data preprocessing explanation demonstrates how sensitive attributes like gender are controlled to avoid discrimination and bias (Dwivedi and Rawat 2015). Similarly, the algorithm description provides information on the specific algorithms used in the AI screening process, ensuring consistency and transparency (Rosen and Krithivasan 2012). The algorithm's accuracy is essential in determining the model's confidence level and its ability to make correct selections consistently (Han et al., 2011). With a better understanding of the selection process, job applicants may perceive a rejection as fairer, which translates into a higher likelihood of acceptance. Therefore, we hypothesize that:

H3: The perception of organizational justice positively mediates the relationship between the process explanation of AI (vs. no explanation) and job applicant intentions to accept rejection letters.

Furthermore, we expect that clear and consistent outcome explanations will be positively related to applicants' acceptance intention. This is because a clear explanation of the outcome will prevent rejected applicants from developing counterfactual thoughts and imagining reasons for their rejection (Gilliland et al. 2001). Equal rejection rates among subgroups can further promote organizational justice by demonstrating that all applicants have an equal chance, regardless of characteristics like age, gender or ethnicity (Gilliland 1993). The information provided about the well-qualified candidates chosen by AI can serve as a reference for other applicants, enhancing perceived fairness and consistency in decision-making.

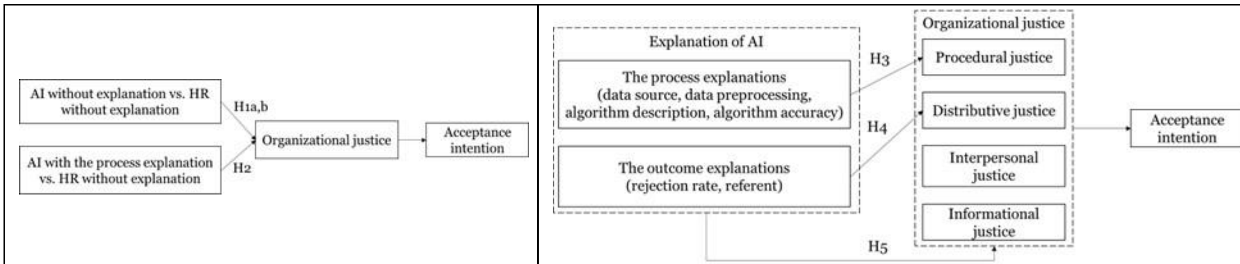
According to equity theory, employees consider a decision fair when their outcomes and inputs are equal compared to others (Adams 1965). In the context of employment, outcomes include monetary rewards (e.g., pay, fringe benefits), non-monetary rewards (e.g., status, job interest), and psychological rewards (e.g., recognition, opportunities for growth). Inputs, on the other hand, represent the contributions made by the individual, such as the effort exerted, educational level, skills, and qualifications relevant to the job (Lawler 1968). Therefore, based on the equity theory, applicants who receive an unfavorable outcome are more likely to accept it if they receive a clear and fair explanation of the outcome (Daly 1995), especially in the context of AI job screening where concerns about fairness and bias are heightened.

The study conducted by Schinkel et al. (2011) yielded significant findings indicating that the provision of detailed rejection information had a progressively detrimental impact on the well-being of applicants, resulting in lower perceptions of fairness. This research contributes valuable evidence to our understanding of how specific negative feedback can adversely affect candidates in a meaningful way. While our explanation focused primarily on outlining the factors encompassed by equity theory and the emphasis on the rejection rate and the referent, rather than highlighting the detrimental effects arising from specific negative feedback. Thus, we propose:

H4: The perception of organizational justice positively mediates the relationship between the outcome explanation of AI (vs. no explanation) and job applicant intentions to accept rejection letters.

As discussed, both process and outcome explanations in a rejection letter can improve applicants' acceptance intentions, which are mediated by organizational justice. While both types of explanations are associated with organizational justice in general, we predict that outcome explanations have a greater effect on organizational justice perceptions than process explanations (Truxillo et al. 2004). This is because when applicants are rejected, it might motivate them to engage in a social comparison with the selected candidate (Tavakoli and Thorngate 2005), and use the comparison to judge whether the decision is fair or not. Rejected applicants are concerned more about their weaknesses and the reasons why they were rejected. The rejection perception literature states that in situations without an outcome explanation, applicants tend to be angered by the result, and often try to obtain information about accepted candidates (Tavakoli and Thorngate 2005). They want to learn more about the gap between them and the selected candidate to identify their weaknesses and improve their performance in the future. In other words, job applicants often prioritize the outcome over the process because the outcome is the most tangible and immediate information related to their career goals and aspirations (Tavakoli and Thorngate 2005). Thus, we posit the following hypothesis:

H5: Applicants will associate greater organizational justice with a rejection when the rejection letter provides an outcome explanation of AI, compared to when the letter provides a process explanation of AI.



(a) HR without explanation vs. AI (without/with the process explanation)

(b) AI only (the process /the outcome explanations)

Figure 1. Research Model

Experiment

Experimental Design

We utilized a mixed experiment with 6 groups where participants were provided with different combinations of explanations in the rejection letter and different recruitment entities (AI or HR). As described in Table 1, we presented all participants with a baseline description and one of six treatment groups (of our study). In Groups 5-6, the treatment is HR managers without explanation, but the baseline between Groups 5 and 6 differs from that in Group 6 people did not receive an explanation, as shown in Table 1. For Group 3, the only difference between the baseline and treatment was the company's name, with participants receiving a rejection letter from either ABC or Hoobi.

As shown in Table 1, AI rejection with a process explanation is used as the baseline, which is consistent with Jiang and Benbasat (2007) and Xu et al. (2014) who also incorporated baseline controls in their studies. The baseline is meant to establish a reference point or comparison group that allows for a more accurate assessment. Building on previous research findings (Gilliland 1993), it has been established that applicants' perception of organizational justice precedes their acceptance of the outcome. Therefore, we introduced perceived justice as a mediating variable, while acceptance served as the outcome variable. The baseline rejection letter is a standard rejection letter using the process explanation of AI. The only exception is group 6, in which people were exposed to an AI rejection without explanation as a baseline.

Before participants read the rejection letter, they watched a video that summarized why a fictitious company uses an AI selection system. Then, they were asked to imagine themselves as one of the applicants. After the subjects were assigned to one of the six rejection groups, each subject read the baseline rejection letter which served as a benchmark for evaluating the treatment rejection letter. The group design was pilot-tested with a small group of participants before the actual data collection to ensure its clarity and content validity. Minor changes were made in the survey following the feedback gathered from the pilot study.

Groups	Baselines	Treatments
1	AI with the process explanation	AI with the process & the outcome explanations
2	AI with the process explanation	AI with the outcome explanation
3	AI with the process explanation	AI with the process explanation
4	AI with the process explanation	AI without explanation
5	AI with the process explanation	HR managers without explanation
6	AI without explanation	HR managers without explanation

Table 1. The Treatments with the Baselines

Sample and Incentives

A power analysis for a between-subjects design determined that 216 subjects (36 subjects for each group) can assure a sufficient statistical power of 0.80 to detect an effect size of 0.25, near the medium effect size (Cohen 2013). We recruited 300 (50/group) participants from an online research panel called Weidiaocha in China. 25 subjects who did not notice the explanation manipulation in the treatment group and 12 others who had a consistent selection of the same response option for all items in the survey (and below average answer time) were excluded from the data analysis, resulting in the final sample size of 263. Participants' ages range from 21 to 35 years. We chose participants who were in the process of graduating or who were actively looking for employment. Participants were exposed to a scenario about the recruitment of management trainees. All participants were over 21 and had at least a bachelor's degree. Overall, sixty-three percent (63%) of the participants were female. There was no significant difference in gender, age, and education distribution for participants across the six treatment conditions. The age range of 25 to 35 in China is the primary demographic of job seekers in the market, and they exhibit a relatively high level of job search activity. This age category is widely acknowledged as a pivotal and propitious phase in career development, often referred to as the golden period and upward phase [1]. In exchange for their participation and to enhance realism in these scenarios, participants were provided with RMB15 for their participation.

Treatment Manipulation

To address the negative outcomes associated with rejection, previous research has suggested the use of "would" and "should" reducing explanations in rejection letters (Gilliland et al. 2001). Drawing from this literature, our research applied these concepts to the context of AI selection. Specifically, we operationalized process explanations as an explanation of the procedure and how the AI made decisions, further enhancing transparency and reducing ambiguity for the applicants as the "should" reducing explanations (Lee et al. 2019). Additionally, we operationalized outcome explanations as an explanation of why the algorithm made certain allocations and whether they were appropriate from the applicant's perspective, with the aim of providing greater clarity information to mitigate the “would" counterfactual thinking (Lee et al. 2019).

Our research builds on the “People + AI Guidebook” from the Google PAIR team (PAIR 2019). Recent studies have highlighted the potential use of the "People + AI Guidebook" as a tool and framework for evaluating AI systems (e.g., Golbin et al. 2020). The guidebook identifies four structures of explanations: (1) articulate data sources, (2) description of the system, (3) model confidence displays and (4) the output. These structures informed the conceptualization of the proposed explanations presented in Table 2.

The first dimension, “articulate data sources”, refers to explanations regarding data collection and evaluation processes. It can be further sub-divided into “data sources” and “data preprocessing”. Explanations regarding the data source provide applicants with information regarding the type of data and its origins. The explanation of it shows the information validity and reliability (Greenberg and Colquitt 2013). Explanation of data preprocessing, on the other hand, provides rejected applicants with information about how raw data was handled. For example, an organization may emphasize how “raw” data was cleaned and how irrelevant or potentially sensitive data (e.g., gender; ethnicity) was deleted during the selection process. Explanations about data sources can thus reduce perceived biases among job candidates.

The second dimension provides “descriptions” of how the AI recruitment system works. It provides specific information about the underlying algorithm of the AI system, and the procedures that are being used to source, screen, and select candidates. Thirdly, “model confidence” provides information about the algorithm's “accuracy” and consistency. This dimension is important as it allows job applicants to assess the reliability and validity of the AI system's decision-making process, thus increasing fairness in the selection process. Finally, the output description provides applicants with information about the “rejection rate”, which is the difference in accuracy between various subgroups (Berk et al. 2021). Additionally, it informs them about the “referent”, which is the background of the accepted candidates. This information helps applicants understand how their application was evaluated and how they compare to other candidates.

Importantly, we can further group these dimensions into process and outcome explanations. Explanations regarding the rejection rates and the referent (i.e., successful candidate) provide rejected applicants with

[1] Reported by the Chinese government (https://rsj.guiyang.gov.cn/rzxzx/xxgg/202107/t20210712_68971573.html).

details about the decision outcomes. Explanations regarding the data sources, pre-processing, algorithm description and algorithm accuracy provide explanations about the inner workings of the AI, and can thus be classified as process information.

Explanations Dimensions	Explanations Details	Definitions
The process explanation	Data source	All types of content contain data objects, text documents, database records, database tables, spreadsheets, schematics, images, and multimedia. (Albornoz et al. 2012).
	Data preprocessing	A set of activities to make raw data suitable for further processing (Dwivedi and Rawat 2015).
	Algorithm description	A finite set of precise instructions for performing a computation or solving a problem (Rosen and Krithivasan 2012).
	Algorithm accuracy	The percentage of correctly classified instances for evaluation (Han et al. 2011).
The outcome explanation	Rejection rate	The percentage of a subset of the general population, refers to the group's age, gender, occupation, nationality, ethnic background, and sexual orientation that are rejected (Congress 2018).
	Referent	The perceived performance of an alternative, which applicants compare with the target object (Kang et al. 2009).

Table 2. Dimensions of Explanations

The data source and data preprocessing descriptions were generated from Google documents (Terms 2021). We build on prior work on Long Short-Term Memory (LSTM) to design our algorithm description (Beaufays et al. 2014). All the websites (e.g., Skill 2020) of AI productions we reviewed had an accuracy higher than 90%. Thus, our target algorithm accuracy was set at 95.6%. Furthermore, we showed the rejection rate of the algorithm outcomes by gender and age (Wang et al. 2020)[2]. We utilized a prior study on rejection letters (Gilliland et al. 2001) to provide information about the hired candidate (referent). The contents of the explanation were determined based on a pretest so that participants were able to understand the explanation. Before participants were given the rejection letter, they were instructed via a video to imagine that they recently graduated and were looking for a job. Furthermore, they learned that the job market was extremely competitive this year, and that the position offered at Hoobi Technology Co. Ltd provides an important and unique opportunity for their careers. They were further informed that due to the large number of applications, Hoobi Technology Co. Ltd employed an AI system for resume selection. After that, participants in our study were presented with a job description that outlined the requirements for the position. These requirements included a bachelor's degree or higher from a reputable university, fluency in the English language, command of all office software, and strong leadership skills. Participants were also asked to assume that they had good communication skills, no internship experience, no honors or awards, and only one skill of English Level 4. Following this, participants received a rejection letter from Hoobi Technology Co. Ltd., which informed them that they were not selected for the position. The rejection letter varied based on the experimental condition to which they had been assigned. Finally, participants completed a survey that assessed their perceptions of organizational justice and acceptance intention. The survey also included questions about their demographic characteristics.

Measurement

The Appendix provides sample measurements used to measure procedural justice, distributive justice, interpersonal justice, informational justice and acceptance intention. For all items, we used an eleven-point Likert scale, with a neutral midpoint of "0". Participants were thus able to compare the two rejection letters (baseline vs. treatment), with a value below the midpoint indicating a higher rating of the baseline rejection

[2] We did not provide the rejection rate by race, as 91.51% of the Chinese population were classified as Han (https://en.wikipedia.org/wiki/List_of_ethnic_groups_in_China).

letter, and values above the midpoint suggesting a higher rating of the treatment rejection letter (Jiang and Benbasat 2007).

Data Analysis and Results

Construct Reliability and Validity

First, we established the internal reliability and validity of the organizational justice dimensions and acceptance intention. The Cronbach's α and composite reliability were all above the cited minimum value of 0.7 (Nunnally 1994), indicating high internal reliability. To formally test the presence of collinearity, we calculated the variance inflation factor (VIF). The results indicated that all of the VIFs were lower than 5.0, with the highest VIF being 4.42. Thatcher and Perrewe (2002) suggest that when VIFs exceed 10, collinearity biases the result. Because the VIFs did not exceed 5.0, our analysis indicated that collinearity did not influence the results. The discriminant validity of the constructs was assessed via a principal component factor analysis using SPSS version 26. We found that the loadings of a given construct's indicators are higher than the loadings of any other, and these same indicators load more highly on their intended construct than on any other construct. The differences in all cases were more than 0.3. Meanwhile, the software SMART PLS 3.0 was employed to perform confirmatory factor analysis. The results of the analysis revealed that all loadings of the indicators were above 0.708 (Hair et al. 2019). Thereby demonstrating acceptable item reliability.

Table 3 presents the diagonal entries as the square roots of the average variance extracted (AVE) of latent variables, while the off-diagonal entries represent the correlations between latent variables. To ensure adequate discriminant validity, the square root of the AVE for each latent variable should be greater than the correlation (Fornell and Larcker 1981). Table 3 indicates that all constructs satisfied this requirement.

Constructs	CR	CA	VIF	PROJ	DISJ	INTJ	INFJ	ACCI
Procedural justice (PROJ)	0.83	0.86	3.88	**0.80**				
Distributive justice (DISJ)	0.77	0.92	1.52	0.717	**0.724**			
Interpersonal justice (INTJ)	0.90	0.95	4.42	0.52	0.65	**0.83**		
Informational justice (INFJ)	0.74	0.88	1.74	0.59	0.75	0.65	**0.77**	
Acceptance intention (ACCI)	0.72	0.89	NA	0.56	0.70	0.72	0.62	**0.75**

Abbreviations: CR, composite reliability; CA, Cronbach's alpha; VIF, variance inflation factor. Diagonal elements (in bold) are the square root of AVE.

Table 3. Internal Consistency and Discriminant Validity of Constructs

As manipulation checks for process explanations and outcome explanations of AI, a one-sample t-test was performed to compare participants' ratings (mean=5.32) with a test value of 4.00 (the scale midpoint) for the process explanations. The results indicated a significant difference (difference=1.32, $p<0.001$). Similarly, for the outcome explanations of AI, the results revealed a significant difference (difference=1.79, $p<0.001$), indicating that the manipulation of process and outcome explanations was effective.

In our study, we examined several factors related to participants' responses to a rejection letter. Firstly, we asked participants' desire for the job via rating scales. The mean score obtained for participants' desire was 5.87 on a 7-point Likert scale, suggesting that participants exhibited a relatively high level of interest and aspiration towards the job. Moreover, we scrutinized participants' perceptions of the realism of both the rejection letter and the AI system employed (4.88, 5.10 on a 7-point Likert scale). Thus, it seems that our approach allowed us to create a research environment that closely mirrored real-life experiences.

To assess the potential common method bias (CMB), we employed a marker variable in our research. This variable was designed to capture a hypothetical scenario related to attending a fan meet-and-greet event in the presence of a heavy rainstorm. Specifically, we asked participants to imagine attending the event with a purchased ticket and whether they would like to attend the event. We analyzed the correlations between this marker variable and other variables, and found little correlation (i.e., all lower than 0.07) among them (Spector 2006). This finding suggests that there is no CMB present in our study.

Hypotheses Tests

Table 4 shows the means and standard deviations for the five constructs presented in the model. To test hypotheses 1a-b, we analyzed the results of Group 6, in which the rejection letter provided by AI and HR both lacked explanations. A one-sample t-test was performed to compare the test value of 0 (the midpoint of the scale) with the participant's rating of the rejection letter delivered by AI and HR without explanation. As we use an eleven-point Likert scale to measure the items, the midpoint of 0 corresponds to a "neither agree nor disagree" response. Values below 0 mean that subjects perceived AI to be more just, whereas values above 0 mean that subjects perceived HR to be more just. The one-sample t-test suggests that as compared to HR, AI has a higher level of perceived procedural justice (mean difference=-0.74, $p<0.05$), but a lower level of interpersonal justice (mean difference=1.46, $p<0.01$) informational justice (mean difference=1.87, $p<0.01$), and acceptance intention (mean difference=1.08, $p<0.05$). No difference exists between HR and AI in terms of distributive justice (mean difference = 0.10, $p > 0.05$). The results thus provide initial support for our H1a that people have greater acceptance intentions when a rejection letter (without explanation) is delivered by an HR manager compared to an AI. We also find partial support for H1b that people perceive rejection letters as more just (in informational and interpersonal justice) when they are delivered by an HR manager, compared to an AI.

To test hypothesis H2 (i.e., people show greater preferences for AI rejections with explanations that HR rejection without explanations), results from the one-sample t-test show that people in Group 5 associate significantly greater procedural justice (mean difference=-2.22, $p<0.05$) and distributive justice (mean difference=-0.91, $p<0.05$) when AI rejection include process explanations, but insignificantly greater informational justice (mean difference=-0.52, $p>0.05$) compared to HR rejections without explanations. There was no significant difference observed in terms of perceptions of interpersonal justice, as indicated by the negligible mean difference of 0.02. The findings thus offer partial support for H2.

To test H3, we conducted a bootstrapping mediation analysis of groups 1&3 vs. groups 2&4 to examine the mediating role of organizational justice (Preacher and Hayes 2008). We utilized the PROCESS macro for SPSS with 5000 bootstrapped samples to estimate the indirect effect of explanations on acceptance via organizational justice perceptions (a×b) (Preacher and Hayes 2004). Table 5 shows that the significant indirect effect of the process explanation on acceptance had a 95% confidence interval that did not include zero ([0.94, 2.21], [0.41, 1.72], [0.09, 1.40], [0.23, 1.42]). The direct effect of the process explanation on acceptance intention was not significant (b=-0.24, b=-0.68, b=0.05, b=0.02, $p>0.05$); hence, procedural justice, distributive justice, interpersonal justice and informational justice fully mediated the effect of process explanation on acceptance intention, providing support for H3.

Similarly, to test H4, we conducted a bootstrapping mediation test of groups 1&2 vs. groups 3&4 in Table 5. The indirect effect of the outcome explanation on acceptance intention was significant and had a 95% confidence interval that did not include zero ([0.96,2.15], [2.24, 3.67], [1.03, 2.24], [1.96,3.51]). Distributive justice and informational justice fully mediated the effects of outcome explanation on acceptance (b=-0.28, b=0.05, $p>0.05$), while procedural justice and interpersonal justice partially mediated the effects on acceptance (b=0.76, b=0.70, $p<0.05$). The results thus offer partial support for H4.

To test the relative importance of process and outcome explanations on justice perceptions and acceptance (H5), we conducted an ANOVA test between Group 2 and Group 3, which shows that the greater perception of distributive justice (mean difference=2.60, $p<0.01$), interpersonal justice (mean difference=2.60, $p<0.1$) informational justice (mean difference=2.98, $p<0.01$), and acceptance intention (mean difference=2.17, $p<0.01$) of Group 2 is statistically significant, but not on procedural justice (mean difference=0.54, $p>0.05$), providing partial support for H5.

We calculated the effect sizes and statistical power for the differences among various experimental groups in terms of acceptance intention. Cohen (2013) guidelines categorize effect sizes of 0.02, 0.15, and 0.35 as small, medium, and large, respectively. Our results indicate that all effect sizes of the group differences exceed the threshold of 0.35, indicating a relatively large effect size.

Our study reveals that providing both process and outcome explanations in AI rejection decisions leads to higher perceptions of procedural justice, distributive justice, interpersonal justice, informational justice, and acceptance compared to only providing one type of explanation. Additionally, the ANOVA test between Group 1 (both process and outcome explanations) and Group 2 (outcome explanations only) indicates that the rejection letter with both explanations has a significantly higher procedural justice (mean difference=1.52, p<0.05). Furthermore, the ANOVA test between Group 1 and Group 3 (process explanation only) illustrates that the rejection letter with both explanations has a significantly higher procedural justice, distributive justice, interpersonal justice, informational justice, and acceptance intention (mean difference=2.07, 3.08, 2.30, 3.10, 2.87, p<0.05). Thus, giving process explanations and outcome explanations together is better than separating them.

Group	Baseline	Treatment	Distributive justice	Procedural justice	Interpersonal justice	Informational justice	Acceptance intention
1	AI, process	AI, process & outcome	3.48 (1.47)	2.37 (1.57)	2.90 (1.82)	3.53 (1.47)	3.24 (1.59)
2	AI, process	AI, outcome	3.00 (2.08)	0.85 (2.81)	2.19 (2.70)	3.42 (1.62)	2.55 (2.81)
3	AI, process	AI, process	0.40 (1.2)	0.31 (1.1)	0.59 (1.3)	0.43 (1.3)	0.38 (1.3)
4	AI, process	AI, none explanation	-1.35 (3.04)	-1.94 (2.67)	-0.27 (3.69)	-1.24 (3.39)	-0.24 (3.58)
5	AI, process	HR, none explanation	-0.91 (2.87)	-2.22 (2.67)	0.02 (3.22)	-0.52 (3.32)	-0.12 (3.05)
6	AI, none explanation	HR, none explanation	0.10 (2.32)	-0.74 (2.18)	1.87 (2.23)	1.46 (2.41)	1.08 (2.80)

Table 4. Means, Standard Deviations

•Note #1: 11-point Likert scale ranging from −5 to +5, where the neutral point (0) indicates that the subject perceives that the second treatment does not differ from the first baseline. The higher the absolute value of a score, the more perceptions of the rejection letter.

IV	M	DV	IV+M->DV		Mediation	LLCI	ULCI
			IV->DV	M->DV			
The process explanation	Procedural justice	Acceptance	-0.24	0.70***	Full	0.94	2.21
	Distributive justice		-0.68	0.77***	Full	0.41	1.72
	Interpersonal justice		0.05	0.74***	Full	0.09	1.40
	Informational justice		0.02	0.71***	Full	0.23	1.42
The outcome explanation	Procedural justice		0.46***	54***	Partial	0.96	2.15
	Distributive justice		-0.28	0.76***	Full	2.24	3.67
	Interpersonal justice		0.43***	0.65***	Partial	1.03	2.24
	Informational justice		0.05	0.70***	Full	1.96	3.51

Table 5. Results of the Mediation Test

•Note #1: ***p<0.001, **p<0.01, *p<0.05

•Note #2: LLCI, lower limit confidence interval; ULCI, upper limit confidence interval.

Discussion

Our study provides robust evidence in support of our focal hypotheses. Specifically, we find that the acceptance intention among applicants who receive a rejection letter from an AI system without any explanation is significantly lower than that of applicants who receive a rejection letter from a human resource (HR) representative without explanation, and this effect is mediated by organizational justice perceptions, particularly distributive justice, interpersonal justice, and informational justice (H1a-b). This result suggests that despite the common perception that AI systems provide equal treatment to all applicants, the lack of personal touch and perceived coldness of the AI system can lower applicants' perception of respect and fairness, ultimately reducing their acceptance intention (Nadarzynski et al. 2019).

Furthermore, we find that process explanations offered by the AI system increase procedural justice and distributive justice perceptions compared to when no explanation is offered by HR. However, it does not improve interpersonal justice and informational justice perceptions (H2). Nevertheless, providing any form of information is better than offering none, as it signals organizational transparency, open communication, and respect for employees, ultimately increasing applicants' perception of interpersonal and informational justice (Tyler 2003). The process explanation of AI yields comparable levels of interpersonal justice and informational justice when compared to no explanation offered by HR.

We also find that organizational justice perceptions fully mediate the effects of process explanation on acceptance intentions (H3), and that distributive justice and informational justice fully mediate the effects of outcome explanation (H4). The latter results might point towards a 'halo effect', which would suggest that once people perceive a rejection as distributive and informationally just, they may feel like they have been treated fairly. Sweeney and McFarlin (1993) proposed the distributive halo model, positing that distributive justice has a halo influence on procedural justice. It suggests that individuals' perceptions of distributive justice have a significant impact on their evaluations of procedural justice. Furthermore, it shows that employees are inclined to endorse existing procedures only in the presence of perceived distributive justice (Reithel et al. 2007). Consequently, according to this model, the perception of distributive justice by applicants can contribute to their evaluation of procedural fairness. In other words, when applicants believe that outcomes are fairly distributed, they are more likely to perceive the procedures as equitable and just. Interpersonal justice represents the social dimension of distributive justice, encompassing behaviors that demonstrate concern for individuals in relation to the outcomes they receive (Greenberg and Cropanzano 1993). When individuals perceive that outcomes are distributed fairly, it tends to create a favorable context for interpersonal interactions, where individuals feel respected and valued. Therefore, distributive justice can have halo effects on interpersonal justice, implying that perceptions of fair distribution of outcomes can positively influence perceptions of fair interpersonal treatment.

Finally, our results show that as compared to process explanations, outcome explanations have a relatively greater effect on distributive justice, interpersonal justice and informational justice perceptions and acceptance intention (H5), arguably because applicants pay more attention to the reasons why they were rejected than to procedural aspects of the hiring process. Given that rejected applicants have missed the opportunity for an interview, the primary concern regarding fairness lies in the outcome rather than the treatment by AI (Clay-Warner et al. 2005). Consequently, outcome explanations, being more specific and individualized, hold greater significance in shaping overall adequacy judgments, thereby enhancing perceptions of interpersonal justice and informational justice (Shapiro et al. 1994a). Our study found that the perception of procedural justice is not significantly higher with outcome explanations compared to process explanations. This is likely because the process explanation already provides detailed information about the selection procedure, and the outcome explanation cannot significantly improve the perception of procedural justice beyond what is provided in the process explanation. Personal evaluations are more strongly associated with distributive justice, whereas systemic evaluations are more strongly linked to procedural justice (Sweeney and McFarlin 1993).

To summarize, our results suggest that offering both process and outcome explanations in a rejection letter is important for increasing applicants' justice perceptions and acceptance intention, especially when the rejection is delivered by an AI system. Providing process and outcome explanations together is the most effective approach in enhancing applicants' perceptions of organizational justice and acceptance intention, compared to providing process and outcome explanations separately.

Contributions

Theoretical Contributions

Our study offers significant theoretical contributions. First, it advances knowledge in the domains of algorithm aversion (Castelo et al. 2019) and algorithm appreciation (Logg et al. 2019) by identifying the important role of process and outcome explanations in AI rejection decisions. Noble et al. (2021) conducted one of the few studies that compared rejection and decisions delivered by AI or humans. However, their study did not account for the possible effect of (different) explanations, and their impact on organizational justice and/or acceptance. While people show algorithm aversion in the absence of explanations, we find that people prefer AI rejection decisions with process explanations over HR decisions without explanations.

This finding points towards an important boundary condition of algorithm aversion, highlighting the importance of opening the "black-box" of algorithm and providing people with transparent and clear explanations about underlying processes and outcomes of AI-driven HR processes (Arrieta et al. 2020).

Secondly, we theorized and empirically confirmed that people are more likely to accept rejection decisions from an AI with explanations (vs. HR without explanations), because of the positive impact of explanations on people's organizational justice perceptions. This study proposed and empirically testified an underlying mechanism by which different organizational justice perceptions mediated the effects between different explanation dimensions and the acceptance intention. In the context of goods division, Lee et al. (2019) solely examined the association between explanations, procedural and distributive justice, without exploring the effects of different explanation dimensions or their impact on interpersonal justice and informational justice. Most studies in the HR context (Schinkel et al. 2013) to date also only explained the relationship between generic explanations and organizational justice. Our study shows that different explanations affect organizational justice perceptions differently, thus offering a more nuanced account. The findings add to the growing body of knowledge that highlights the importance of spillover effects of explanation on interpersonal justice and informational justice perceptions in HR contexts (Folger and Cropanzano 1998) and advance understandings of the consequences of explanations mediated by different organizational justice.

Third, our research advances knowledge and theorizing in the domain of explainable AI. Interestingly, when comparing the relative impact of process and outcome explanations on acceptance intentions, our findings show that outcome explanations seem to matter more. Recent studies examine the process and outcomes explanations in AI systems, but they mainly focus on the effectiveness of each explanation dimension (Wang et al. 2020; Zhang et al. 2020). While the different dimensions of the explanation have been extensively discussed, limited research has been conducted to investigate and compare differences in process and outcome explanations in regard to organizational justice and acceptance, particularly in the AI domain. Our study addresses this gap by showing that the effects of outcome explanation are stronger than the effects of process explanation in the AI recruitment systems context.

Practical Contributions

To ensure the effective use of AI, it is imperative for companies to provide explanations, particularly process explanations at a minimum. Outcome explanations are even more effective, and the ideal scenario is for both types of explanations to be provided. While providing both process and outcomes explanation seems ideal, if managers have to choose, our findings suggest that they should prioritize or emphasize the latter. That is because applicants who are rejected seem to be influenced more by the outcome explanation, and specifically information about the rejection rate(s) and hired candidates. The latter allows rejected candidates to 'benchmark' themselves and identify potential areas for personal growth and improvement. Failure to provide explanations, however, will result in decreased perceptions of organizational justice and lower acceptance intentions among applicants. Therefore, to ensure fairness and increase acceptance from applicants, companies must prioritize the provision of transparent and clear explanations in their AI systems. This can help to enhance applicants' perceptions of fairness and reduce negative outcomes such as retaliation or negative word-of-mouth. Ultimately, policymakers should consider the role of explanations when developing laws and regulations that affect corporations' recruitment policies and procedures. Our study also offers implications for managers. Our findings highlight the importance of process and outcome explanations for the AI recruitment system. Managers should include such explanations when communicating rejection decisions to applicants in order to enhance fairness perceptions, increase acceptance rates, and avoid potential retaliation or negative word-of-mouth.

Limitations and Future Research

Our study has several limitations that provide avenues for future research. Firstly, the experiment employed a scenario-based approach. This approach aimed to create a controlled environment that allowed for the examination of participants' behavior in a standardized manner. While the scenario-based approach provides a controlled setting for our research, it may not capture the full complexity and emotional impact of real-life experiences. The generalizability of findings from scenario-based experiments to real-world contexts should be approached with caution. Future studies should try to replicate these findings in real-world recruitment situations. Secondly, most recruited participants are aged between 21 to 35, who are the primary group of job seekers in the market, and they exhibit a relatively high level of job search activity. However, our results might not hold for more senior citizens, who may have a more negative attitude towards AI. Thirdly, the existing study focuses only on the process explanation and the outcome explanation. Future studies could extend the research and explore the simultaneous effects of other explanation dimensions, such as counterfactuals (Leben 2023). Finally, we treated the AI algorithm as a black box AI (machine learning), and hence we are unable to test the effects in a white box AI context. Future research should extend this study by testing it in the context of the white box AI algorithm.

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Appendix: Measurement Items

Constructs	Measurement (adaptation)	References
Procedural justice	Which rejection letter contains consistent process of the AI selection system?	(Colquitt 2001)
Distributive justice	Given the skills you have, which rejection letter contains a more justified outcome for your rejection?	
Interpersonal justice	Which rejection letter treated you in a polite manner?	
Informational justice	Which rejection letter was candid in his/her communications with you?	
Accuracy of data source	The data source (ResumeSource dataset) mentioned in Hoobi's rejection letter t is reliable.	(Wang and Strong 1996)
Bias suppression of data preprocessing	In Hoobi's rejection letter, according to the explanation of data preprocessing, the data is objective after data preprocessing. (Data preprocessing refers to processing the data in the dataset before training the algorithm, such as filling in missing data.)	(Lee et al. 2002)
Algorithm description complexity	In Hoobi's rejection letter, the description of the algorithm is difficult to understand.	(See et al. 2009)
Algorithm consistency	In Hoobi's rejection letter, according to the accuracy of the algorithm, the artificial intelligence resume screening system performed well.	(Kocielnik et al. 2019)
Equality of rejection rate	In Hoobi's rejection letter, AI treats gender-specific applicants equally.	(Kostenko et al. 2016)
Referent equity	In Hoobi's rejection letter, the result of being rejected by artificial intelligence is fair compared to applicants who qualified.	(Heslin 2003)
Acceptance intention	Overall, the rejection result of which company's AI resume selection system would you be more likely to accept?	(McComas et al. 2007)