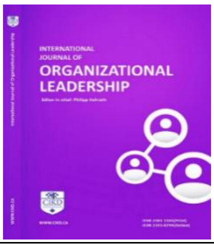
International Journal of Organizational Leadership 14(2025) 224-243



INTERNATIONAL JOURNAL OF ORGANIZATIONAL LEADERSHIP

WWW.CIKD.CA

journal homepage: https://www.ijol.cikd.ca

Who Are Favored by AI and Why Them? Influencing Factors of Job Applicants' Interview Performance and Intention to Use AVI-AI

Zhenyao Cai[1], Xinying Li[2], Yimin Mao[3*], Haoqing He[4], Qiao Fu[5]

[1,2,5]SILC Business School, Shanghai University, Shanghai, China
[3]China Unicom Network Communications Co., Ltd. Shanghai Branch, Shanghai, China
[4]Bellamy's Organic Food Trading (Shanghai) Co., Ltd, Shanghai, China

Keywords:
AVI-AI, Trust, Fairness, Technology uncertainty, Human-robot interaction self-efficacy

Received
05 February 2025
Received in revised form
05 March 2025
Accepted
08 March 2025

***Correspondence:**
maoym11@chinaunicom.cn

ABSTRACT

Artificial intelligence technology is increasingly used in the organizational recruitment and personnel selection process to simplify various human resource activities. Among these innovative applications, Asynchronous Video Interviews with AI (AVI-AI) have emerged as a popular tool. In this study, the theory of planned behavior and its extended framework are adopted to explore the impacts of overall fairness, technology certainty, and human-robot interaction self-efficacy on job applicants' intention to use AVI-AI, thereby testing the candidate's reaction to this technical change. A total of 443 participants were involved in 2 distinct studies. Rigorous data analysis and statistical tests were carried out. The results unequivocally confirm that the impact of these factors on the job applicants' intention to use AVI-AI is highly significant. Creatively, this study breaks new ground by providing solid empirical evidence for the positive correlation between job applicants' intention to use AVI-AI and their subsequent interview performance. Furthermore, this study confirms the mediating role of trust between overall fairness, technology uncertainty, human-robot interaction self-efficacy, and job applicants' intention to use AVI-AI. In addition, the implications of these findings are thoroughly dissected from the perspectives of both organizations and technology developers, offering valuable insights for future organizational recruitment practices and technological improvements.

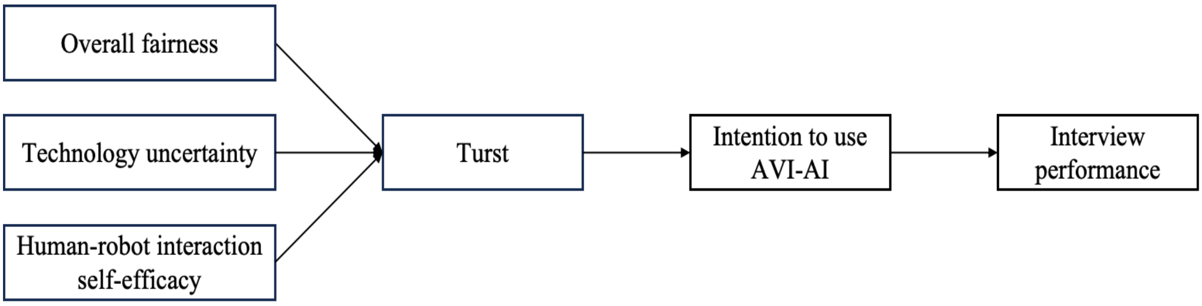
Research has found that AI technology has the significant potential to simplify various human resources activities. For example, AI can be used to filter job application data to quantify work experience (Sajjadiani et al., 2019). To date, most research has focused on the AI technology itself (Calders & Žliobaitė, 2013; Krawczyk, 2016). However, few studies have been conducted on people's perception of AI technology (Fast & HorvitzV, 2017). With the popularization of the Internet and the extensive use of digital recruitment platforms, a beneficial alignment has been established between job seekers and employers. AI (Artificial Intelligence) technology is increasingly used in the process of recruitment, which is defined as "a broad class of technologies that allow computers to perform tasks that normally require human cognition, including adaptive decision-making" (Tambe et al., 2019).

Recruiting the right talents is a key aspect of competitive advantage for employers, as talents determine whether an organization has the knowledge, skills, abilities, and other features that are necessary to survive and succeed. In order to successfully recruit the right talent, it is becoming increasingly important to ensure that job seekers have a positive reaction to the way they are treated by the organization during the recruitment process (Walker et al., 2013). Therefore, from the perspective of talent strategy, employers must not only increase the size and quality of initial candidates but also maintain the interest of candidates throughout the recruitment process (Köchling et al., 2023; Walker et al., 2015). However, there is a paucity of research on applicant reactions to the use of AI in recruitment (Langer et al., 2018, 2019; Lee, 2018).

Applicant reactions can be defined as the candidate's attitude, response, or perception of the recruitment process or selection tool (McCarthy et al., 2017; Roulin et al., 2023). As a key influential factor of applicant reaction, the perception of justice (Gilliland, 1993) will directly affect the attitude and behavior both during the selection process and post-recruitment decision, including organizational attraction, job performance, intention to accept job offer and motivation to recommend employers to others (Bauer et al., 1998; Konradt et al., 2017; McCarthy et al., 2013). Prior research indicates that the justice dimension, especially two-way communication of interactional justice, mediated the effect of interview type on different applicant reactions (Acikgoz et al., 2020). Moreover, numerous researches have confirmed the mediating effect of trust between justice perception and employee’s job performance (Cropanzano et al., 2007; Lance Frazier et al., 2010; Stinglhamber et al., 2006; Tang & Jiang, 2024). However, no existing research has investigated this mediating effect in the context of AVI-AI. In addition, the innovation of new technology is inherently uncertain. Hence, introducing AI into the recruitment process creates risk and anxiety for job seekers, thereby potentially affecting their willingness to use AVI-AI. According to the literature on technological trust (Chen et al., 2011), familiarity with technology and previous experience often enhance trust. In contrast, a lack of familiarity with and experience with the technology reduces trust. As a new technology applied to the recruitment process, AVI-AI is unfamiliar to job seekers, leading to distrust. Human-computer interaction self-efficacy is another critical factor affecting the job seekers' intention to use the AVI-AI. Technology-centered perception, in other words, self-efficacy, has consistently been a vital factor in technology acceptance and technology adoption (Chen et al., 2011; Compeau & Higgins, 1995).

Therefore, this research set out to verify the effect of the intention to use the AVI-AI on the interview performance and to discuss the influence of the overall fairness, technology uncertainty, and human-robot interaction self-efficacy on the intention to use the AVI-AI. On the basis of the technology acceptance model theory, we argue that trust is a significant variable to predict the applicant's acceptance of AVI-AI. Clearly, another objective of this research is to investigate whether trust is able to play a mediator role between 3 predictor variables and the intention to use AVI-AI. The importance and originality of this research are that it was conducted with empirical methods to explore the relationship between various variables and the intention to use AVI-AI, which has sufficient theoretical and practical significance. This study aims to make theoretical contributions in three ways. First, to our knowledge, an outstanding contribution of our work is demonstrating the influence of the applicant's intention to use AVI-AI on their interview performance. It extends the current literature on AVI-AI and applicants' reactions. Second, integrating the TPB, this study examines three important factors in the applicant's intention to use AVI-AI. Previous studies primarily concentrate on system characteristics (Rizi & Roulin, 2024; Suen & Hung, 2023) of AVI (like transparency and immediacy). This study extends variables derived from the applicant's personal perception and traits. Third, in addition to the three factors, this study extends the current literature by testing the mediating role of trust. The research aspires to contribute to future work on the application of artificial intelligence technology in the field of recruitment. The theoretical model is shown in Figure 1.

Figure 1
Research Model



Literature Review and Hypothesis

As the latest innovation in the job selection process, AVI-AI allows unlimited pre-recruitment interviews to be conducted anytime and anywhere in the world (Brenner et al., 2016). Combining visual and audio recognition technology with machine learning, AVI-AI integrates the functions of asynchronous video interviews and AI decision agents (Celiktutan & Gunes, 2015). The use of machine learning and AI for job selection may offer practicality beyond human-based methods and traditional assessments (Campion et al., 2016; Speer, 2018). By virtue of supercomputing power and matching algorithms based on social information processing, AVI-AI is able to automatically assess applicants' verbal and non-verbal cues and match them to more suitable positions (Walther, 2011). For these reasons, AVI-AI is becoming increasingly popular in the industry.

The reaction of the applicant to the recruitment selection process will affect many attitudes and behaviors before entering the job, such as the intention of accepting the offer, the attraction of the organization, the willingness to recommend the company to others, or even the intention to file a lawsuit with the company (McCarthy et al., 2017). Hence, it is imperative to investigate the reaction of candidates during AVI-AI. In recent years, most research on candidates' reactions to AVI-AI has focused on fairness, trust, and attitudes. On the one hand, the candidates have a negative reaction to the AVI-AI, which is mainly reflected in their lower perceived fairness. Many studies have found that candidates find AVI-AI less unfair and less advantageous than other forms of interview (such as face-to-face and simultaneous videoconferencing interviews)(Basch et al., 2022; Kleinlogel et al., 2023). On the other hand, candidates also have a positive reaction to AVI-AI, which is mainly reflected in the belief that AVI-AI is highly novel, innovative, flexible, and efficient (Kim & Heo, 2021). However, many empirical studies have found that job applicants tend to have a relatively negative attitude toward organizations that use AVI-AI (Acikgoz et al., 2020; Wesche & Sonderegger, 2021). In summary, the research on job seekers' reactions to AVI-AI is limited to variables related to traditional interview reactions, and there is little exploration of antecedent factors. In addition, no studies have examined the "interview performance in AVI-AI" as a consequence variable. Therefore, this article aims to broaden the study of the antecedents and consequences of AVI-AI use intention by using empirical research.

The Theory of Planned Behavior (TPB) illustrates the connection between beliefs and behavior, arguing that behavior can be planned thoughtfully. The best function of TPB is to predict behavior, particularly in measuring individual behavioral intentions. Behavioral intention was conceptualized as an independent variable or belief-based indicator, including attitudes, perceived behavioral control, and subjective norms. Attitudes reflect an individual's subjective tendency towards a specific behavior, which means that a person with a positive attitude is likely to adopt a specific behavior (Ajzen, 2002). Subjective norms represent the extent to which an individual or a group can influence an individual's behavioral decisions to take a particular action toward an individual (Ajzen, 2002). Perceived behavioral control is defined as the belief that individuals think it is easy or difficult to accomplish a specific behavior (Ajzen, 2011). Based on the recent research about AVI-AI and the theory of planned behavior, this study proposed three factors that affect the applicants’ intention to use the AVI-AI.

First, perceived fairness, as a key dimension in the applicant reaction model, reflects the candidates' fair feelings about the recruitment results, evaluation tools, internal recruitment decision procedures, and how they are treated during the recruitment process. In other words, the overall sense of fairness is a subjective perception of the job seeker, which reflects the applicant's attitude to the interview process and results. According to TPB, attitude represents the subjective tendency of the applicants to use AVI-AI, and the more positive they feel about the fairness of AVI-AI, the more inclined they are to use AVI-AI. Second, perceived risk and uncertainty may affect people's intention to accept the new technology. Technical uncertainty refers to the uncertainty that was triggered by new technological change and the skills and knowledge required for users to successfully use the new technology. Job applicants' uncertainty about AVI-AI can bring risk perception, leading them to think of difficulties in using AVI-AI. According to TPB, technology uncertainty is a kind of perceived behavioral control that affects the belief of whether it is easy or difficult to use AVI-AI. For example, the higher the applicant's perceived uncertainty about the potential risks of using AVI-AI, the lower their intention to use AVI-AI. Third, human-robot interaction self-efficacy is also an important factor affecting people's willingness to accept new technologies. Self-efficacy refers to a person's ability to engage in a certain behavior in a given situation and achieve desired results. This concept is similar to the concept of perceived behavioral control, which is consistent with Ajzen’s (2002) argument that self-efficacy and perceived behavioral control are synonyms.

Therefore, according to TPB, the higher the self-efficacy of applicants in the interaction with AVI-AI, the higher their intention to use AVI-AI. In this study, overall fairness, technology uncertainty, and human-robot interaction self-efficacy were selected as the factors influencing the employment intention to use.

Intention to Use and Interview Performance

Based on the Technology Acceptance Model (TAM) theory, the user's actual behavior of the technology system is directly or indirectly affected by the user's behavioral intention, attitude, perceived system usefulness, and the perceived ease of use of the system. Over the past few decades, researchers have found that a person is highly likely to accept the technology if he has the intention to use it (Chen, 2011). Intention to use is an indicator of how much effort a person is willing to make when actually using any technology. In other words, when users realize that the new technology is useful, they will be more inclined to use the technology for success. Similarly, in the context of AVI-AI, this study predicts that the more willing the applicant is to use AVI-AI, they will put a corresponding degree of effort in this process, and thus, the better performance. On the other hand, if the applicant has less intention to use AVI-AI, they will perform sluggishly during the interview, resulting in a low interview performance score. However, there is a contradiction that under the real circumstances of job-hunting pressure, no matter whether the job seeker has the intention to attend the AVI-AI, they may conceal or ignore their true intention and participate in the AVI-AI. Focused on this conflict, whether the job applicants' intention to use the AVI-AI can still affect the interview performance as predicted above is the first question that will be discussed in this study. This paper proposes the hypothesis that:

H1. The applicant's intention to use AVI-AI positively affects the AI-rated interview performance.

Factors of Intention to Use

Effect of Overall Fairness on Intention to Use

The perception of fairness usually plays an important role in the model of job applicant reaction (McCarthy et al., 2017). Signaling theory suggests that in the absence of organizational transparency, job seekers can only infer signals from available information (Chapman et al., 2003). In the context of job interviews, when applicants are in a weak status with limited awareness of organizational information, they must rely on cognitive shortcuts to quickly make decisions about the concept of justice (Cropanzano et al., 2001; Lind et al., 2001). Evidence proves that job seekers will respond more positively when a recruitment interview process is identified as equitable (McCarthy et al., 2017; Roulin et al., 2023; Schinkel et al., 2016). For example, the perception of procedural fairness was positively correlated with organizational attractiveness and recommendation intentions and negatively correlated with litigation intention (Ababneh et al., 2014). Interactive fairness mediated the relationship between interviewer enthusiasm and individual reaction outcomes, including recommendation intentions, organizational attractiveness, and the possibility of accepting work (Farago et al., 2013). Based on these findings, it is reasonable to infer that the overall fairness perception of the job applicant is also related to their reaction outcomes. Generally, if a candidate perceives the overall fairness of the AVI-AI at a higher level, they will have more intention to use AVI-AI. On the contrary, if a candidate considers the AVI-AI lacks overall fairness, their intention to use the AVI-AI will be weak. Therefore, we make this hypothesis:

H2a. The overall fairness of the applicant positively affects the applicant's intention to use the AVI-AI.

Effect of Technology Uncertainty on Intention to Use

Studies have shown that providing information about AI, increasing transparency, and explaining the details of how this data will be used can increase job seekers' intention toward AI in a hiring circumstance (Langer et al., 2017). In the process of technology adoption, users are limited by their own knowledge and awareness. Because users cannot accurately control the cognition, development, and effect of technology, they experience technology uncertainty. For example, when job seekers first receive an invitation to AVI-AI, if they are not familiar with the AVI-AI process and algorithm decision behind a system, it may lead to the uncertainty of the interview method and their skills and knowledge needed to deal with the interview. Uncertainty creates unbearable feelings of anxiety, which leads to users resisting or reluctance to use new technology (Köchling et al., 2023). That is, the more uncertainty the user feels about the new technology, the less willing he/she is to use this technology. In consequence, this paper argues that in the AVI-AI situation, the lower the applicants' perception of the uncertainty, the stronger the intention to use it. On the contrary, the higher the perception of technology uncertainty, the weaker the intention to use it. Therefore, this article makes the hypothesis:

H2b. The perception of technology uncertainty negatively affects the applicant's intention to use the AVI-AI.

Effect of Human-Robot Interaction Self-Efficacy on Intention to Use

Human-robot interaction self-efficacy introduces a kind of individual's sense of self-related ability, which is similar to an individual's confidence or belief in the ability needed to achieve a specific goal. For example, even if the applicant does not have the knowledge and skills to participate in the AVI-AI, they have a strong subjective belief that "I can perform well in the AVI-AI," then the applicant is highly likely to choose to use the AVI-AI. Based on the Technology Acceptance Model (TAM) theory, self-efficacy is a determinant of perceived ease of use both before and after the actual use of technology (Venkatesh & Davis, 1996), and perceived ease of use can directly affect the user's intention to use the technology. In addition, motivation theory suggests that self-efficacy is an intrinsic motivational factor that predicts a user's attitudes and behavioral intentions toward using new technology. Although self-efficacy is considered to be an important variable in technology acceptance, studies have shown that it does not have a significant moderating effect on the perceived usefulness of AVI-AI and attitude (Brenner et al., 2016). Although self-efficacy is a highly domain-specific construct, considering similarities between AVI-AI and intelligent robots, this paper hypothesizes that the correlation between human-robot interaction self-efficacy and the intention to use new technologies is also applicable to AVI-AI. Therefore, this paper hopes to introduce the concept of self-efficacy of user human-robot interaction into the AVI-AI context. In view of these findings, the present study argues that the higher the applicant has human-robot interaction self-efficacy, the stronger the intention to use AVI-AI, and the lower the applicant has human-robot interaction self-efficacy, the weaker the intention to use AVI-AI. Therefore, this paper makes the hypothesis:

H2c. The self-efficacy of human-robot interaction positively affects the applicant's intention to use the AVI-AI.

Factors of Trust

Trust is a broad concept defined differently in psychology and sociology, but generally, it involves two entities, the trustor and the trustee (Colquitt et al., 2007; Glikson & Woolley, 2020). Trust is important in relationships with humans and non-humans, such as automation (Hoff & Bashir, 2015). Similar to interpersonal interactions, human-robot interaction adopted parallel specifications (Madhavan & Wiegmann, 2007; Suen & Hung, 2023), which allows for the application of interpersonal trust theory to human-robot relationships.

Effect of Overall Fairness on Trust

Numerous studies have found that an overall sense of justice is highly associated with trust. An early study (Alexander & Ruderman, 1987) found a positive relationship between trust of senior managers and both procedural and distributive justices.

Procedural justice is promoted when organizations use consistent, accurate, impartial, and correctable procedures and represent the issues and ethics of company concerns. Thus, AVI-AI procedure rules may be particularly relevant to cognitive-based trust (McCarthy et al., 2017), as AVI-AI emphasizes consistency and accuracy, which base cognitive trust. Studies have also shown that interpersonal justice can be promoted when organizations treat employees with dignity and respect and avoid inappropriate comments or comments during the programming process (Greenberg & Cropanzano, 1993). These interpersonal rules may be particularly relevant to emotion-based trust, as it is difficult to develop feelings of mutual care and concern in rude, disrespectful or inappropriate communication. Job seekers feel worse interpersonal relationships during the AVI-AI because they have limited interaction with decision makers (i.e., unable to ask and fully express themselves), which may hardly give them a feeling of being cared for and concerned. However, because AVI-AI is hardly subjective, they are also less likely to have a poor interview experience due to the bias against applicants during the scoring process. Thus, interactive justice may be particularly relevant to emotion-based trust and may be less pronounced for cognitive-based trust. To sum up, the overall perception of fairness and trust is highly related. In this paper, it is speculated that in the context of the AVI-AI, the stronger is the overall fair perception of the AVI-AI; on the contrary, the weaker is the overall fair perception of the AVI-AI, the lower is his trust in the AVI-AI. Therefore, this article makes the hypothesis:

H3a. Applicants' overall fairness positively affects their trust in AVI-AI.

Effect of Technology Uncertainty on Trust

In the AVI-AI situation, there are potential uncertainties such as spatial and temporal separation between job seekers and interviewers, and the novelty of AI technology (Hunkenschroer & Luetge, 2022). The sense of distance, the non-interpersonal nature of the online environment, and the potential uncertainty about new technologies (i.e., AI technologies) make risk inevitable in AVI-AI. There are two forms of uncertainty in AVI-AI, the uncertainty of the technical tools and the uncertainty of the knowledge needed to use the tools (Langer et al., 2019). Uncertainty may pose the risk of failing the interview. Therefore, AVI-AI includes the concept of technical uncertainty, which does not exist in the traditional interview process. Technical uncertainty can trigger risk perception. Studies have shown that trust is associated with good perception, including satisfaction, long-term orientation, and risk reduction (Ganesan, 1994). In other words, the higher the user's perception of risk, the less they trust the new technology. Based on the above views, this paper speculated that in the AVI-AI situation, the higher the technology uncertainty of the candidate, the weaker the trust in the AVI-AI; otherwise, the higher the perception of the technology certainty, the stronger the trust in the AVI-AI. Therefore, this hypothesis:

H3b. Applicants' perception of technology uncertainty negatively affects their trust in the AVI-AI.

Effect of Human-Robot Interaction Self-Efficacy on Trust

Self-efficacy is an individual's confidence or belief in the ability needed to achieve a specific goal in a specific field or the belief that I can do it. This means that the concept of self-efficacy itself is particularly relevant to beliefs and trust. In the field of human-computer interaction, some studies have confirmed that self-efficacy in human-computer interaction is a person's perceived ability to use and interact with robots and is a key factor affecting the trust relationship between humans and robots (Schaefer, 2013). The intelligent technology used in the artificial intelligence interview has a high similarity with the intelligence of the robot. Therefore, given that human-computer interaction self-efficacy affects trust (Gompei & Umemuro, 2018), this study sought to examine the impact of job candidate interpersonal interaction self-efficacy on trust in the AVI-AI context. This paper speculated that in the context of AVI-AI, the higher the human-computer interaction, the higher the trust in the AVI-AI, and the lower the candidate self-efficacy, the lower the trust in the AVI-AI. Therefore, this article makes the hypothesis:

H3c. Applicants' human-robot interaction self-efficacy positively affects their trust in AVI-AI.

The Mediating Effect of the Trust

The intention to use is derived from the Theory of Reasoned Action (TRA), as exemplified by the study of the Technology Acceptance Model (TAM). TRA suggests that external variables such as personal values or beliefs about the broader work environment should directly influence beliefs leading to specific intentions. Most of the research work in TRA / TAM has focused on two key beliefs, perceived use and ease of use, and their antecedents. However, other variables can also predict the intention to use. The present research attempts to examine other factors that influence the intention to use, such as trust. The theory of risk suggests that risk perception has a negative impact on the intention to perform risk behaviors (Keil et al., 2000). Like risk perception, trust is an assessment mechanism to assess how much users expect of a positive outcome. Recent research further adds to the concept of trust as a predictor of technical acceptance (Ghazizadeh et al., 2012; Hoff & Bashir, 2015; Shin, 2021). Parasuraman and Riley (1997) interpreted that the concern of trust not only enabled us to solve the problem of technology abandonment but also the abuse of technology. Specifically, trust can predict the dependence on technology and the actual results of technology use. Based on the above analysis, this study infers that the more applicants trust in AVI-AI, the more their intention to use AVI-AI. On the contrary, the lower the applicants' trust in AVI-AI, the less their intention to use AVI-AI. Therefore, this article assumes that:

H4. Applicants' trust in AI technology has a positive impact on their intention to use AVI-AI.

Based on H1-H4, it is reasonable to speculate in this study that high overall fairness, technology uncertainty, and human-robot interaction self-efficacy can increase the applicants' intention to use AVI-AI by strengthening the trust. In conclusion, this study hypothesizes:

H5. Trust mediates the relationship between (a) overall fairness, (b) technology uncertainty, and (c) human-robot interaction self-efficacy and the applicants' intention to use AVI-AI.

To propose our theoretical model, two questionnaires were designed to collect data overall. Specifically, the sample of study 1 is mainly to test the main effect of the intention to use AVI-AI on the interview performance; the sample of study 2 is mainly to test the influencing factors of applicants' intention to use AVI-AI, namely the mediating role of trust between (a)overall fairness, (b)technology uncertainty, (c)human-robot interaction self-efficacy and intention to use. Study 1 and Study 2 are independent of each other, and their samples are also designed for different participants. Similarly, the results of Study 1 and Study 2 do not influence each other.

Study 1 Method

Participants and Procedure

Study 1 was conducted in May 2022, which is the time to start sending resumes and preparing for summer internships for college students in Shanghai, China. Research assistants recruited college students as participants by distributing posters on college campuses. The poster clearly stated that participants could obtain a free AVI-AI opportunity, professional resume coaching, and a final interview feedback report if they completed the whole experiment. To simulate a real recruiting atmosphere, participants were asked to submit a resume and some important personal information, such as name, mobile phone number, and email address. Then, within a week of collecting the resume information, research assistants sent a link to the AVI-AI website and an instruction profile to the participants via email or message, along with interview deadlines. The link to the AVI-AI contains a measurement questionnaire and an AVI-AI, which takes about 25 minutes to complete. In addition, this study put special emphasis on the survey guideline that the data is only used for academic research and that all information will be kept strictly confidential, which guarantees the authenticity and validity of the sample data.

To ensure the validity of the sample, the whole study carried out four rounds of the same data collection process around the above steps. The final effective sample consisted of N = 122 participants, of which 67.21% (N = 82) were female. Among 122 participants, 52.46% (N = 58) were between 18 and 22 years old, 40.98% (N = 50) were between 23 and 27 years old, and 6.86% (N = 8) were 28 years old or above.

Measurements

Unless otherwise stated, all the measurements of the two studies used a five-point Likert-type scale (1= Strongly disagree, 5= Strongly agree). Meanwhile, the measurements of all variables in the two study used the scales widely tested in previous research. Since the original measurement items were in English, we followed the translation program to form a Chinese questionnaire and then test the participants.

Intention to use. Applicants' intention to use AVI-AI was measured using a three-item scale from Venkatesh et al. (2003). A sample item is "I think I would like to continue to use the AVI-AI if I can choose in the future job interview" (ɑ = .80).

Interview performance rated by AVI-AI. Applicants' interview performance in study 1 was scored by an AVI-AI system of Jinyu Intelligence from China[1], which has an advanced chapter-level semantic recognition algorithm and Talent DNA competency model to range interviewees. In this system, participants' interview performance was rated by the AVI-AI system in four dimensions: problem-solving, learning ability, retrospection, and innovation ability. At the end of the interview, the AI will rate the participants on each of the four dimensions, and the final results can be directly exported by system's administrator. The evaluation interface of the AI interview system used in this research is shown in Figure 2. The performance dimensions and assessment questions obtained from the AVI-AI results are shown in Table 1.

Figure 2

Interface of AVI-AI System

Table 1

The Performance Dimensions and Assessment Questions of AVI-AI in Study 1

Dimensions	Definition	Assessment question
Problem-Solving	Grasp the key to the problem in a limited time and give feasible solutions from multiple angles.	Please give an example of how you solved (or helped solve) a difficult problem (either work or life examples). Please describe how you dealt with different key people in the process and the result of solving the problem.
Learning Ability	Understanding, mastery, and application of new knowledge/skills through effective approaches, methods, and tools.	What learning tools (such as the mind mapping APP) will you use when learning skills or knowledge related to work or life? Give you three examples of how do you use these learning tools?
Retrospection	Be good at learning from failure, learn from experience, and take measures to improve, adjust, and break through the failure.	The ancients said: no one is perfect. Everyone can make mistakes. Please give an example of how you have made a mistake or made a wrong decision (decision), and what is the final result? What lessons and lessons have you learned?
Innovation Ability	Can produce potentially valuable new ideas or actively adopt new methods, new technologies, and new ways to carry out creative work.	Please give an example of creatively solving problems or proposing innovative ideas in your past studies or internships. What was the situation like then? What innovative solutions/ideas have you proposed? How did it come out?

[1] Commercial product named "AI RecruiTas", which is an eco-partner of SAP. More information can be found in https://www.airecruitas.com/

Control variable. In order to exclude the influence of variables other than the main variable on participants' intention to use, three control variables were introduced in this study: gender, age, and education.

Study 1 Results

To understand the interaction pattern and linear relationship between variables in this study, Pearson correlation analysis was conducted. The results of the correlation coefficient between the variables in Study 1 (see Table 2) showed that retrospective (r = .22, p < .05) and innovation ability (r = .25, p < .01) were significantly and positively related to intention to use among the four dimensions of AVI-AI interview performance.

Table 2

Descriptive Statistics and Correlation Matrix for Study 1.

Variables	*M*	*SD*	1	2	3	4	5	6	7	8
1. Gender [a]	0.67	.47	1							
2. Age [b]	1.57	.72	-.12	1						
3. Education [c]	1.43	.50	-.09	.66**	1					
4. Problem Solving	1.823	.65	.00	.11	-.02	1				
5. Learning Ability	2.00	.72	.17	-.08	-.12	.16	1			
6. Retrospection	1.98	.78	.02	-.02	-.06	.34**	.24**	1		
7. Innovation Ability	1.53	.56	.17	-.19*	-.15	.23*	.21*	.16	1	
8. Intention to Use	3.81	.72	-.11	.14	-.09	.03	.02	.22*	.25**	1

Note. *p < .05; **p < .01.

[a] 0 = Male; 1 = Female.

[b] 1 = 18-22 years old; 2 = 23-27 years old; 3 = 28-32 years old; 4 = 33-38 years old; 5 = above 39 years old.

[c] 1 = High School diploma; 2 = Junior college diploma; 3 = Bachelor's degree; 4 = Master's degree; 5 = Doctoral degree

Based on the correlation, the present study examined hypothesis 1 by using linear regression analysis with SPSS 26.0. In the case of introducing three control variables, the effects of intention to use on innovation ability and retrospective reflection were tested, respectively. Table 3 summarizes the results of the regression.

According to Table 3, the intention to use AVI-AI positively affects the applicants' retrospection (β = .25, p < .05) and innovation ability (β = .24, p < .01). However, there is no significant regression relationship between intention to use and problem-solving (β = -.01, p > .05) and learning ability (β = .03, p > .05). From the perspective of research purpose, study 1 is mainly to test the effect of intention to use on interview performance, that is, to verify whether hypothesis 1 was support. Currently, our data support the direct effect of intention to use on only two in four dimensions of interview performance. This is probably on account of the lopsided data caused by insufficient sample size. Hence, in order to avoid similar problems in subsequent studies, this research increased the sample size and modified the target sample when conducting data collection in Study 2.

Table 3

Regression Results for Study 1

Variables	Problem-Solving	Learning Ability	Retrospection	Innovation Ability
Constant	1.85***	1.94***	1.07*	.71*
Intention to use	-.01	.03	.25*	.24**
Gender	.02	.25	.07	.21*
Age	.20	.00	-.05	-.20*
Education	-.22	-.14	-.01	.06
R^2	.03	.04	.05	.14
Adjusted R^2	-.01	.01	.02	.11

Note. *p < .05; **p < .01; ***p < .001.

Study 2 Method

Participants and Procedure

Study 2 was conducted in October 2022 and recruited participants with an online survey platform in China who were employees with working experience. To ensure that the participants filled in the survey truthfully, this study explained that the data we obtained was only used for academic research and made a confidentiality commitment in the introduction of the questionnaire. In addition to the main variables, three demographic information variables were also designed in the questionnaire as control variables, namely gender, age, and education level. Finally, the valid sample of study 2 consisted of N = 321 participants, which 59.50% (N = 191) were female. Among 321 participants, 3.43% (N = 11) were between 18 and 22 years old, 24.30% (N = 78) were between 23 and 27 years old, 37.38% (N = 120) were between 28 and 32 years old, 21.50% (N = 69) were between 33 and 38 years old, and 13.40% (N = 43) were 39 years old or above.

Measurements

Overall fairness. Applicants' overall fairness was measured using Kim's (2004) three-item scale. A sample item is "Overall, I think the AVI-AI is fair to me" (α = .60).

Technology uncertainty. Applicants' perception of technology uncertainty was measured using Stock and Tatikonda's (2008) three-item scale. A sample item is "I do not know enough about AVI-AI technology or products" (α = .81).

Human-robot interaction self-efficacy. Applicants' human-robot interaction self-efficacy was measured using Pütten and Bock's (2018) six-item scale. A sample item is "I think I am able to adjust myself to adapt to the AI recruitment" (α = .78).

Trust. Applicants' trust in AVI-AI was measured by a six-item scale, integrating Mcknight et al.'s (2011) four-item scale and Choung et al.'s (2022) two-item scale. A sample item is "The AVI-AI is credible" (α = .84).

Intention to use. Applicants' intention to use AVI-AI was measured using Lu et al.'s (2005) three-item scale. A sample item is "Using AVI-AI is worthy" (α = .73).

Study 2 Results

The results of model fit of Study 2 showed that $\chi 2$ / df = 2.18, less than 3; RMSEA = .06, less than 0.1; CFI = .93, greater than .9; TLI = .91, greater than .9; IFI = .93, greater than .9; NNFI = .91, greater than .9. The two indexes are higher than the standard, indicating that the theoretical model constructed has a good fit, significant factor load degree, and good aggregation validity. The measured data is of high quality and suitable for the next analysis.

To demonstrate the discriminatory validity of the model, we compared the various alternative four-factor models by randomly combining the two variables (see Table 4) and conducted CFA to measure validity (see Table 5). The model comparison results of Study 2 showed that the CFI of the five-factor model was .93, greater than the other four-factor models; TLI was .91, greater than the other four-factor models; REMSEA was 0.06, less than the other four-factor models. Clearly, the five-factor model fits better than the other four-factor models. Therefore, we confirmed the discriminative validity of study 2 and applied the five-factor model for further analysis.

Table 4

Results of Model Fitting and Model Comparison

Model	χ^2	$\triangle\chi^2$	df	CFI	TLI	RMSEA
Five-factor model	389.94	/	179	.93	.91	.06
Four-factor model (combining HRISE and PTU)	419.62	29.68**	183	.92	.90	.06
Four-factor model (combining HRISE and OF)	47.25	8.32**	183	.90	.88	.07
Four-factor model (combining HRISE and Trust)	443.60	53.67**	183	.91	.89	.07
Four-factor model (combining HRISE and ITU)	444.03	54.089**	183	.91	.89	.07
Four-factor model (combining PTU and OF)	511.99	122.05**	183	.88	.87	.08
Four-factor model (combining PTU and Trust)	501.97	112.03**	183	.89	.87	.07
Four-factor model (combining PTU and ITU)	50.97	56.33**	183	.89	.87	.07
Four-factor model (combining OF and Trust)	446.27	27.98**	183	.91	.89	.07
Four-factor model (combining OF and ITU)	417.92	27.98**	183	.92	.90	.06
Four-factor model (combining Trust and ITU)	42.73	3.79**	183	.92	.90	.06

Note. *$p < .05$; **$p < .01$. OF = Overall fairness, PTU = Perception of technology uncertainty, HRISE = Human-robot interaction self-efficacy, ITU = Intention to use.

Table 5

CFA results for Study 2

Variables	CR	AVE
Overall fairness	.61	.34
Perception of technology uncertainty	.81	.59
Human-robot interaction self-efficacy	.78	.38
Trust	.85	.48
Intention to Use	.74	.59

Table 6

Descriptive Statistics and Correlation Matrix for Study 2

Variables	M	SD	1	2	3	4	5	6	7	8
1. Gender [a]	1.60	.49	1							
2. Age [b]	3.17	1.05	-.08	1						
3. Education [c]	2.90	.65	-.03	-.19**	1					
4. OF	4.09	.63	.06	.07	.05	1				
5. PTU	1.43	.88	-.02	.04	-.17**	-.31**	1			
6. HRISE	3.87	.60	.02	-.00	.06	.44**	-.74**	1		
7. Trust	3.62	.63	.07	-.01	.07	.48**	-.66**	.73**	1	
8. Intention to Use	4.03	.67	-.02	.01	.15**	.54**	-.54**	.67**	.70**	1

Note. *$p < .05$; **$p < .01$. OF = Overall fairness, PTU = Perception of technology uncertainty, HRISE = Human-robot interaction self-efficacy.

[a] 0 = Male; 1 = Female.

[b] 1 = 18-22 years old; 2 = 23-27 years old; 3 = 28-32 years old; 4 = 33-38 years old; 5 = above 39 years old.

[c] 1 = High School diploma; 2 = Junior college diploma; 3 = Bachelor's degree; 4 = Master's degree; 5 = Doctoral degree

The results of the correlation coefficient between the variables in Study 2 can be seen in Table 6. Overall fairness is significantly and positively related with trust (r = .48, p < .01) and intention to use (r = .54, p < .01). Perception of technology uncertainty is significantly and positively related to trust (r = -.66, p<0.01) and intention to use (r = -.54, p < .01). Human-robot interaction self-efficacy is significantly and positively related with trust (r = .73, p < .01) and intention to use (r = .67, p < .01). The above results indicate a significant correlation between the variables of the conceptual model, which is suitable for further regression analysis. Study 2 tested the hypotheses by linear regression analysis with SPSS 26.0.

Table 7

Regression Results for Study 2

Variables	Trust	Intention to use	
Constant	-.12	1.41***	.26
Age	-.01	.02	.00
Gender	.05	-.08	-.07
Education	-.02	.11**	.09*
Overall fairness	.28***		.32***
Perception of technology uncertainty	-.22***		-.06
Human-robot interaction self-efficacy	.53***		.53***
Trust		.65***	
R^2	.60	.50	.54
Adjusted R^2	.59	.50	.54

Note. *p < .05; **p < .01; ***p < .001.

According to Table 7, overall fairness (β = .28, p < .001) and human-robot interaction self-efficacy (β = .53, p < .001) positively affects trust, and technology uncertainty (β = -.22, p < .001) negatively affects the trust. Therefore, H3 was supported. In addition, trust (β = .65, p < .001), overall fairness (β = 0.32, p<0.001), and human-robot interaction self-efficacy (β = .53, p < .001) positively affect the intention to use. However, the regression relationship between technology uncertainty and intention to use was not significant. Therefore, H2 was partially supported, and H4 was supported.

The mediation effect was tested using PROCESS. The results are shown in Table 8. All three mediation effects were significant, supporting the H5.

Table 8

Bootstrapping Results for Study 2

Effect	β	SE	LLCI	ULCI
Overall fairness => Trust => Intention to use	.08	.02	.04	.12
Perception of technology uncertainty => Trust => Intention to use	.08	.03	.05	.16
Human-robot interaction self-efficacy => Trust => Intention to use	.18	.04	.09	.24

Note. confidence interval is 95%

Discussion

The current research aims to investigate the potential influencing factors of applicants' intention to use AVI-AI within the framework of the Theory of Planned Behavior. Based on the findings from two studies, it is evident that overall fairness and human-robot interaction self-efficacy directly impact applicants' intention to use AVI-AI. Furthermore, all three independent variables are shown to influence applicants' intention to use AVI-AI through trust. Another significant discovery is that this behavioral intention also partially affects their interview performance. The general discussion encompasses the following sections.

Theoretical Contributions

Existing research on AVI-AI adoption has predominantly utilized frameworks such as UTAUT to examine factors influencing applicants' acceptance of AI interview tools. This study extends prior work by adopting the Theory of Planned Behavior (TPB) to investigate additional internal determinants of applicants' intention to use AVI-AI, empirically validating three critical factors and demonstrating TPB's efficacy in explaining adoption intentions.

The outcome variables of past studies in the AVI-AI field have principally focused on behavioral intention and have not examined its intervention on candidate interview performance. Using objective AVI-AI products to obtain AI rated interview performance generated by algorithm, and to detect the relationship between interviewees' intention to use new technologies and interview performance is a major innovation of this paper. It is interesting to note that the results of study 1 show that the intention to use will actually affect the interview performance, but only in some dimensions (retrospection and innovation ability). For retrospection, we argue that the interviewee's reflection is a timely self-adjustment mechanism in the AVI-AI. Promptly discovering questions and adjusting coping strategies are conducive to improving interview performance. For innovation ability, compared to candidates who are less tolerant of AI, those who are more willing to use AVI-AI should be more open to innovation. As for the insignificant dimensions (problem-solving and learning ability), a linear regression model may not explain the relationship between these two more complex abilities and use intention. Otherwise, measurement algorithm defects and insufficient sample size are also possible reasons.

Study 2 further advances understanding by incorporating trust as a mediator within the TPB framework, aligning with prior findings (Tang & Jiang, 2024). While technological uncertainty exhibited no direct effect on usage intention, its indirect effect became significant when mediated by trust, thereby enriching theoretical antecedents of trust in human-computer interaction contexts. This dual-study approach not only reinforces the role of trust in technology adoption models but also provides empirical evidence bridging behavioral intentions to tangible performance outcomes in AI-mediated assessments.

Practical Implications

The empirical findings offer actionable insights for optimizing AI-driven video interviews (AVI-AI) in recruitment practices. First, to enhance applicants' perception of fairness and transparency, organizations should proactively disclose the AI decision-making logic (e.g., criteria weighting, algorithmic role in evaluation) through pre-interview guidelines or interactive tutorials. For instance, embedding a brief explainer video within the AVI-AI platform could demystify how behavioral traits like retrospection and innovation ability are assessed, aligning with Study 1's findings.

Second, AVI-AI developers must prioritize technical stability and functional clarity to reduce applicants' perceived technological uncertainty. This includes implementing real-time system diagnostics to minimize glitches during interviews and prominently showcasing the tool's reliability metrics (e.g., uptime rates, error-recovery protocols) on recruitment platforms. Study 2's mediation analysis underscores that trust in the technology's dependability amplifies applicants' adoption intentions, which in turn improves performance in innovation-related tasks. To operationalize this, developers could integrate a "transparency dashboard" displaying real-time data processing (e.g., "Your response is being analyzed for problem-solving skills") to reassure candidates about the system's accuracy and intentionality.

Third, HR practitioners should adopt a human-centric intermediation strategy to bridge the trust gap between applicants and AI systems. For example, recruiters could host pre-interview webinars to clarify the AVI-AI's evaluation criteria (e.g., how learning ability is measured through response patterns) and emphasize human oversight in final hiring decisions. During evaluations, automated feedback reports could highlight strengths in retrospection (e.g., "Your self-adjusted answer improved the response coherence") to reinforce the tool's value as a developmental aid rather than a black-box evaluator.

Finally, organizations must recognize that AVI-AI systems reflect their employer brand and ethical stance. For instance, aligning AI design with corporate values (e.g., programming algorithms to prioritize diversity-aware assessments) can attract candidates who value innovation and inclusivity. Publishing annual transparency reports on AVI-AI outcomes would further position the company as a responsible adopter of AI, enhancing its reputation in competitive talent markets. By integrating these strategies, firms can transform AVI-AI from a mere efficiency tool into a catalyst for equitable, candidate-centric recruitment experiences.

Limitation and Future Research

Although the interview performance data used in Study 1 was measured by a mature AI scoring model certified by experts and used in corporate recruitment practices, it lacks the verification of academic validity. From the perspective of technical progress, the measurement algorithm used in this study only reached the L4 level, so the conclusions of this study are more applicable to the current level of AVI-AI. Since artificial intelligence large language models are in a period of rapid development, the iteration and advancement of future algorithms may lead to different findings. Hence, future research could use more general and advanced algorithms to measure interview performance in AVI-AI.

This study found that the stronger the applicant's intention to use AVI-AI, the better the final interview performance, but the intermediate explanation mechanism is not discussed. From the perspective of business practice, the recruiter hopes to objectively evaluate the quality of a candidate based on the interview results and judge whether he can have better work performance if he works in the company in the future. Why is it that applicants with more intention to use AVI-AI have higher expected work performance? Does the strength of this intention indicate any ability or trait of the candidate? This issue deserves to be discussed in depth.

Conclusion

Theoretically, this research extends the TPB framework by integrating trust as a critical mediator between technological uncertainty (e.g., system stability) and intention to use AVI-AI while empirically validating novel linkages between applicants' intention to use AVI-AI and algorithm-rated performance in retrospection and innovation ability — dimensions previously unexplored in technology adoption models. Methodologically, it pioneers the use of objective AI-generated performance metrics to demonstrate that acceptance intentions do not uniformly predict complex competencies (e.g., problem-solving), challenging assumptions about linear human-AI behavioral outcomes. Practically, it identifies perceived fairness (via algorithmic transparency) and human-computer interaction self-efficacy (via user-centered design) as actionable levers for enhancing both applicant trust and recruitment outcomes. These findings address a critical gap in extant research, which predominantly treats AVI-AI adoption intentions and interview performance as isolated phenomena. Future studies should investigate contextual moderators and longitudinal effects of AVI-AI exposure on candidate development.

Declarations

Acknowledgements

Not applicable.

Disclosure Statement

No potential conflict of interest was reported by the authors.

Ethics Approval

Not applicable.

Funding Acknowledgements

Not applicable.

Citation to this article

Cai, Z., Li, X., Mao, Y., He, H., & Fu, Q. (2025). Who are favored by AI and why them? Influencing factors of job applicants' interview performance and intention to use AVI-AI. *International Journal of Organizational Leadership*, *14*(1), 224-243. https://doi.org/10.33844/ijol.2025.60465

Rights and Permissions

Reference

Ababneh, K. I., Hackett, R. D., & Schat, A. C. H. (2014). The role of attributions and fairness in understanding job applicant reactions to selection procedures and decisions. *Journal of Business and Psychology*, *29*(1), 111–129. https://doi.org/10.1007/s10869-013-9304-y

Acikgoz, Y., Davison, K. H., Compagnone, M., & Laske, M. (2020). Justice perceptions of artificial intelligence in selection. *International Journal of Selection and Assessment*, *28*(4), 399–416. https://doi.org/10.1111/ijsa.12306

Ajzen, I. (2002). Perceived behavioral control, self-efficacy, locus of control, and the theory of planned behavior 1. *Journal of Applied Social Psychology*, *32*(4), 665–683. https://doi.org/10.1080/08870446.2011.613995

Ajzen, I. (2011). The theory of planned behaviour: Reactions and reflections. *Psychology & Health*, *26*(9), 1113–1127. https://doi.org/10.1080/08870446.2011.613995

Alexander, S., & Ruderman, M. (1987). The role of procedural and distributive justice in organizational behavior. *Social Justice Research*, *1*(2), 177–198. https://doi.org/10.1007/BF01048015

Basch, J. M., Melchers, K. G., & Büttner, J. C. (2022). Preselection in the digital age: A comparison of perceptions of asynchronous video interviews with online tests and online application documents in a simulation context. *International Journal of Selection and Assessment*, *30*(4), 639–652. https://doi.org/10.1111/ijsa.12403

Bauer, T. N., Maertz, 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), 892–903. https://doi.org/10.1037/0021-9010.83.6.892

Brenner, F. S., 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. https://doi.org/10.3389/fpsyg.2016.00863

Calders, T., & Žliobaitė, I. (2013). Why unbiased computational processes can lead to discriminative decision procedures. *Studies in Applied Philosophy, Epistemology and Rational Ethics*, *3*, 43–57). https://doi.org/10.1007/978-3-642-30487-3_3

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), 958–975. https://doi.org/10.1037/apl0000108

Celiktutan, O., & Gunes, H. (2015). Automatic prediction of impressions in time and across varying context: Personality, attractiveness and Likeability. *IEEE Transactions on Affective Computing*, *8*(1), 29–42. https://doi.org/10.1109/TAFFC.2015.2513401

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), 944–953. https://doi.org/10.1037/0021-9010.88.5.944

Chen, K., Chen, J. V., & Yen, D. C. (2011). Dimensions of self-efficacy in the study of smart phone acceptance. *Computer Standards & Interfaces*, *33*(4), 422–431. https://doi.org/10.1016/j.csi.2011.01.003

Chen, L.-H. (2011). Enhancement of student learning performance using personalized diagnosis and remedial learning system. *Computers & Education*, *56*(1), 289–299. https://doi.org/10.1016/j.compedu.2010.07.015

Choung, H., David, P., & Ross, A. (2022). Trust in AI and its role in the acceptance of AI technologies. *International Journal of Human–Computer Interaction*, 1–13. https://doi.org/10.1080/10447318.2022.2050543

Colquitt, J. A., Scott, B. A., & LePine, J. A. (2007). Trust, trustworthiness, and trust propensity: A meta-analytic test of their unique relationships with risk taking and job performance. *Journal of Applied Psychology*, *92*(4), 909–927. https://doi.org/10.1037/0021-9010.92.4.909

Compeau, D. R., & Higgins, C. A. (1995). Application of social cognitive theory to training for computer skills. *Information Systems Research*, *6*(2), 118–143. https://doi.org/10.1287/isre.6.2.118

Cropanzano, R., Bowen, D. E., & Gilliland, S. W. (2007). The management of organizational justice. *Academy of Management Perspectives*, *21*(4), 34–48. https://doi.org/10.5465/amp.2007.27895338

Cropanzano, R., Byrne, Z. S., Bobocel, D. R., & Rupp, D. E. (2001). Moral virtues, fairness heuristics, social entities, and other denizens of organizational justice. *Journal of Vocational Behavior*, *58*(2), 164–209. https://doi.org/10.1006/jvbe.2001.1791

Farago, B., Zide, J. S., & Shahani-Denning, C. (2013). Selection interviews: Role of interviewer warmth, interview structure, and interview outcome in applicants' perceptions of organizations. *Consulting Psychology Journal: Practice and Research*, *65*(3), 224–239. https://doi.org/10.1037/a0034300

Fast, E., & HorvitzV, E. (2017). Long-term trends in the public perception of artificial intelligence. *Proceedings of the AAAI Conference on Artificial Intelligence*, *31*(1).

Ganesan, S. (1994). Determinants of long-term orientation in buyer-seller relationships. *Journal of Marketing*, *58*(2), 1–19. https://doi.org/10.1177/002224299405800201

Ghazizadeh, M., Lee, J. D., & Boyle, L. N. (2012). Extending the Technology Acceptance Model to assess automation. *Cognition, Technology & Work*, *14*(1), 39–49. https://doi.org/10.1007/s10111-011-0194-3

Gilliland, S. W. (1993). The perceived fairness of selection systems: An organizational justice perspective. *The Academy of Management Review*, *18*(4), 694. https://doi.org/10.2307/258595

Glikson, E., & Woolley, A. W. (2020). Human trust in artificial intelligence: Review of empirical research. *Academy of Management Annals*, *14*(2), 627–660. https://doi.org/10.5465/annals.2018.0057

Gompei, T., & Umemuro, H. (2018). *Factors and development of cognitive and affective trust on social robots* (pp. 45–54). https://doi.org/10.1007/978-3-030-05204-1_5

Greenberg, J., & Cropanzano, R. (1993). The social side of fairness: Interpersonal and informational classes of organizational justice. *Justice in the Workplace: Approaching Fairness in Human Resource Management*.

Hoff, K. A., & Bashir, M. (2015). Trust in automation. *Human Factors: The Journal of the Human Factors and Ergonomics Society*, *57*(3), 407–434. https://doi.org/10.1177/0018720814547570

Hunkenschroer, A. L., & Luetge, C. (2022). Ethics of AI-enabled recruiting and selection: A review and research agenda. *Journal of Business Ethics*, *178*(4), 977–1007. https://doi.org/10.1007/s10551-022-05049-6

Keil, M., Wallace, L., Turk, D., Dixon-Randall, G., & Nulden, U. (2000). An investigation of risk perception and risk propensity on the decision to continue a software development project. *Journal of Systems and Software*, *53*(2), 145–157. https://doi.org/10.1016/S0164-1212(00)00010-8

Kim, J.-Y., & Heo, W. (2021). Artificial intelligence video interviewing for employment: perspectives from applicants, companies, developer and academicians. *Information Technology & People*, *35*(3), 861–878.

Kim, T.-Y. (2004). *The effects of cognitive appraisal on justice judgements: How and why do Asians differ from United States Americans?* The University of North Carolina at Chapel Hill.

Kleinlogel, E. P., Schmid Mast, M., Jayagopi, D. B., Shubham, K., & Butera, A. (2023). "The interviewer is a machine!" Investigating the effects of conventional and technology-mediated interview methods on interviewee reactions and behavior. *International Journal of Selection and Assessment*, *31*(3), 403–419. https://doi.org/10.1111/ijsa.12433

Köchling, A., Wehner, M. C., & Warkocz, J. (2023). Can I show my skills? Affective responses to artificial intelligence in the recruitment process. *Review of Managerial Science*, *17*(6), 2109–2138. https://doi.org/10.1007/s11846-021-00514-4

Konradt, U., Garbers, Y., Böge, M., Erdogan, B., & Bauer, T. N. (2017). Antecedents and consequences of fairness perceptions in personnel selection. *Group & Organization Management*, *42*(1), 113–146. https://doi.org/10.1177/1059601115617665

Krawczyk, B. (2016). Learning from imbalanced data: open challenges and future directions. *Progress in Artificial Intelligence*, *5*(4), 221–232. https://doi.org/10.1007/s13748-016-0094-0

Lance Frazier, M., Johnson, P. D., Gavin, M., Gooty, J., & Bradley Snow, D. (2010). Organizational justice, trustworthiness, and trust: A multifoci examination. *Group & Organization Management*, *35*(1), 39–76. https://doi.org/10.1177/1059601109354801

Langer, M., König, C. J., & Fitili, A. (2018). Information as a double-edged sword: The role of computer experience and information on applicant reactions towards novel technologies for personnel selection. *Computers in Human Behavior*, *81*, 19–30. https://doi.org/10.1016/j.chb.2017.11.036

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. https://doi.org/10.1111/ijsa.12191

Langer, M., König, C. J., & Papathanasiou, M. (2019). Highly automated job interviews: Acceptance under the influence of stakes. *International Journal of Selection and Assessment*, *27*(3), 217–234. https://doi.org/10.1111/ijsa.12246

Lee, M. K. (2018). Understanding perception of algorithmic decisions: Fairness, trust, and emotion in response to algorithmic management. *Big Data & Society*, *5*(1), 205395171875668. https://doi.org/10.1177/2053951718756684

Lind, E. A., Kray, L., & Thompson, L. (2001). Primacy effects in justice judgments: Testing predictions from fairness heuristic theory. *Organizational Behavior and Human Decision Processes*, *85*(2), 189–210. https://doi.org/10.1006/obhd.2000.2937

Lu, H., Hsu, C., & Hsu, H. (2005). An empirical study of the effect of perceived risk upon intention to use online applications. *Information Management & Computer Security*, *13*(2), 106–120. https://doi.org/10.1108/09685220510589299

Madhavan, P., & Wiegmann, D. A. (2007). Similarities and differences between human–human and human–automation trust: an integrative review. *Theoretical Issues in Ergonomics Science*, *8*(4), 277–301. https://doi.org/10.1080/14639220500337708

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. https://doi.org/10.1177/0149206316681846

McCarthy, J. M., Van Iddekinge, C. H., Lievens, F., Kung, M.-C., Sinar, E. F., & Campion, M. A. (2013). Do candidate reactions relate to job performance or affect criterion-related validity? A multistudy investigation of relations among reactions, selection test scores, and job performance. *Journal of Applied Psychology*, *98*(5), 701–719. https://doi.org/10.1037/a0034089

Mcknight, D. H., Carter, M., Thatcher, J. B., & Clay, P. F. (2011). Trust in a specific technology. *ACM Transactions on Management Information Systems*, *2*(2), 1–25. https://doi.org/10.1145/1985347.1985353

Parasuraman, R., & Riley, V. (1997). Humans and automation: Use, misuse, disuse, abuse. *Human Factors: The Journal of the Human Factors and Ergonomics Society*, *39*(2), 230–253. https://doi.org/10.1518/001872097778543886

Pütten, A. R.-V. Der, & Bock, N. (2018). Development and validation of the Self-Efficacy in Human-Robot-Interaction Scale (SE-HRI). *ACM Transactions on Human-Robot Interaction*, *7*(3), 1–30. https://doi.org/10.1145/3139352

Rizi, M. S., & Roulin, N. (2024). Does media richness influence job applicants' experience in asynchronous video interviews? Examining social presence, impression management, anxiety, and performance. *International Journal of Selection and Assessment*, *32*(1), 54–68. https://doi.org/10.1111/ijsa.12448

Roulin, N., Pham, L. K. A., & Bourdage, J. S. (2023). Ready? Camera rolling… action! Examining interviewee training and practice opportunities in asynchronous video interviews. *Journal of Vocational Behavior*, *145*(May 2022), 103912. https://doi.org/10.1016/j.jvb.2023.103912

Sajjadiani, S., Sojourner, A. J., Kammeyer-Mueller, J. D., & Mykerezi, E. (2019). Using machine learning to translate applicant work history into predictors of performance and turnover. *Journal of Applied Psychology*, *104*(10), 1207–1225. https://doi.org/10.1037/apl0000405

Schaefer, K. (2013). *The perception and measurement of human-robot trust*. University of Central Florida.

Schinkel, S., van Vianen, A. E. M., & Marie Ryan, A. (2016). Applicant Reactions to Selection Events: Four studies into the role of attributional style and fairness perceptions. *International Journal of Selection and Assessment*, *24*(2), 107–118. https://doi.org/10.1111/ijsa.12134

Shin, D. (2021). The effects of explainability and causability on perception, trust, and acceptance: Implications for explainable AI. *International Journal of Human-Computer Studies*, *146*, 102551. https://doi.org/10.1016/j.ijhcs.2020.102551

Speer, A. B. (2018). Quantifying with words: An investigation of the validity of narrative-derived performance scores. *Personnel Psychology*, *71*(3), 299–333. https://doi.org/10.1111/peps.12263

Stinglhamber, F., Cremer, D. De, & Mercken, L. (2006). Perceived support as a mediator of the relationship between justice and trust. *Group & Organization Management*, *31*(4), 442–468. https://doi.org/10.1177/1059601106286782

Stock, G. N., & Tatikonda, M. V. (2008). The joint influence of technology uncertainty and interorganizational interaction on external technology integration success. *Journal of Operations Management*, *26*(1), 65–80. https://doi.org/10.1016/j.jom.2007.04.003

Suen, H.-Y., & Hung, K.-E. (2023). Building trust in automatic video interviews using various AI interfaces: Tangibility, immediacy, and transparency. *Computers in Human Behavior*, *143*(February), 107713. https://doi.org/10.1016/j.chb.2023.107713

Tambe, P., Cappelli, P., & Yakubovich, V. (2019). Artificial intelligence in human resources management: Challenges and a path forward. *California Management Review*, *61*(4), 15–42. https://doi.org/10.1177/0008125619867910

Tang, L., & Jiang, J. (2024). Enhancing the Combined-TAM-TPB model with trust in the sharing economy context: A meta-analytic structural equation modeling approach. *Journal of Cleaner Production*, *442*(January), 141168. https://doi.org/10.1016/j.jclepro.2024.141168

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User Acceptance of Information Technology: Toward a Unified View. *MIS Quarterly*, *27*(3), 425. https://doi.org/10.2307/30036540

Venkatesh, V., & Davis, F. D. (1996). A model of the antecedents of perceived ease of use: Development and test. *Decision Sciences*, *27*(3), 451–481. https://doi.org/10.1111/j.1540-5915.1996.tb00860.x

Walker, H. J., Bauer, T. N., Cole, M. S., Bernerth, J. B., Feild, H. S., & Short, J. C. (2013). Is This How I Will Be Treated? Reducing Uncertainty through Recruitment Interactions. *Academy of Management Journal*, *56*(5), 1325–1347. https://doi.org/10.5465/amj.2011.0196

Walker, H. J., Helmuth, C. A., Feild, H. S., & Bauer, T. N. (2015). Watch what you say: Job applicants' justice perceptions from initial organizational correspondence. *Human Resource Management*, *54*(6), 999–1011. https://doi.org/10.1002/hrm.21655

Walther, J. B. (2011). Theories of CMC and interpresonal relations. *The Handbook of Interpersonal Communication*, *4*, 443–479.

Wesche, J. S., & Sonderegger, A. (2021). Repelled at first sight? Expectations and intentions of job-seekers reading about AI selection in job advertisements. *Computers in Human Behavior*, *125*, 106931. https://doi.org/10.1016/j.chb.2021.106931