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What Drives Job Applicants' Reactions and Behavior Intention During AI-enabled Interview

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Abstract

Artificial Intelligence (AI) has brought significant changes to the field of human resources, especially in the interview process. It has facilitated the implementation of remote interviews, improved applicants' experiences, and contributed to the diversity and inclusiveness of the recruitment process. As organizational research advances, the focus has shifted to applicant reaction, positing their response impact on various outcomes. Organizations must be aware of applicant reactions so that they can be better informed of the potential consequences of their selection procedures. Thus, this research delves into the intricacies of how applicants perceive and respond to AI-enabled interviews and explores various factors that shape applicant and behavior intention.

This research has integrated previous literature and developed a theoretical model that bridges interview type, applicant perceptions, and applicant behavior. The result reveals differences in perceived fairness and social presence between AI interviews and face-to-face interviews in recruitment. Although AI interviews are at a disadvantage in social presence, applicants' trust in AI is unexpectedly higher. The results also emphasize the importance of social presence and fairness in shaping applicants' attitudes and behavioral intentions toward organizations. Moreover, this research combines Fuzzy-Set Qualitative Comparative Analysis (fsQCA) and Structural Equation Modeling (SEM) to deeply highlight the intrinsic relationship between AI recruiters' attributes and applicant behavior intention. It is confirmed that social bandwidth and interactivity stimulate positive perception and behavior. Finally, this study extensively explores the psychological factors with a special focus on regulatory focus theory and regulatory fit in the context of AI-enabled interviews. It is found that regulatory fit significantly increases applicants' feelings of social presence and fairness during their interaction with AI recruiter.

This study has made an important contribution to the field of human resources, providing a comprehensive understanding of the impact of AI interviews through interdisciplinary methodology. It not only reveals the differences between AI interviews and traditional methods in terms of fairness and social interaction but also emphasizes the profound impact of these factors on the decision-making process of applicants. This perspective also provides a new perspective for understanding the psychological motivations and behaviors of applicants and offers valuable insights for organizations on how to optimize AI interview processes to meet the needs of different applicants.

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Abbreviations

AI	Artificial Intelligence
AVE	Average Variance Extracted
CFA	Confirmatory Factor Analysis
CR	Composite Reliability
DSS	Decision Support System
FSN	Failsafe-N
fs-QCA	Fuzzy-Set Qualitative Comparative Analysis
HR	Human Resource
IS	Information System
IT	Information Technology
NLP	Natural Language Processing
PRISMA	Reporting Items for Systematic Review and Meta-Analyses
RFQ	Regulatory Focus Questionnaire
RFT	Regulatory Focus Theory
RJP	Realistic Job Preview
R&S	Recruitment and Selection
SEM	Structural Equation Modelling
SOR	Stimulus-Organism-Response
VR	Virtual Reality

1 General Introduction

1.1 Research Background

As artificial intelligence (AI) systems have achieved superior performance compared to humans in various aspects of the economy and society, the growing technological maturity and wide-ranging applicability of these systems are generating exceedingly high expectations (Lucci et al. 2022). Progress in technology across diverse fields, including machine learning, robotics, big data analytics, decision support systems (DSSs), and the widespread availability of data and information systems (ISs), is unlocking new opportunities for creating value (Jordan and Mitchell 2015, Ågerfalk 2020, Langer and Landers 2021, Chowdhury et al. 2023). Various AI solutions that offer decision-support functions typically associated with human cognition are emerging and have the potential to reshape the nature of work. Therefore, AI is a promising avenue in the human resource (HR) as well.

Since the beginning of the new millennium, AI has emerged as an effective tool in the field of human resources. It aids in matching individuals with suitable positions and optimally managing personnel resources at a reduced cost (Tambe et al. 2019). There has been a noticeable increase in the incorporation of technology into the recruitment and selection (R&S) processes, with approximately 74% of large U.S. enterprises utilizing various electronic selection tools to aid in their hiring procedures (Stone et al. 2015, Black and van Esch 2020). Cutting-edge technologies such as resume screening software and AI-driven interview assessments enable companies to efficiently manage large volumes of applications, resulting in both time and cost savings for recruiters (Zielinski 2017, Abou Hamdan 2019, Ween 2020, Li et al. 2021).

Notably, many companies have developed an AI robot capable of reviewing applicants' resumes, conducting interviews, and even taking on the role of a recruiter, recommending the most fitting applicants for job positions (Langer et al. 2018, Dijkkamp 2019, Li, Lassiter et al. 2021, Hunkenschroer and Luetge 2022). Stockholm's prominent recruitment company, TNG, one of Sweden's largest, has adopted an innovative approach to conduct interviews with prospective job applicants. They have introduced a robotic interviewer (AI recruiter) known as Tengai, featuring a head that either sits on or projects from a table. This head-level placement enables Tengai to engage with interviewees at eye level during the interview process. Thanks to recent technological advancements, AI has surpassed humans in analyzing personality, emotions, and cognitive abilities (Rathi 2018, Bawack et al. 2021, Robles-Granda et al. 2021, Zall and Kangavari 2022, Kleinlogel et al. 2023). Consequently, AI's role in personnel selection continues to expand, and it is anticipated that AI will eventually play a central role in making final selection decisions (Rodney et al. 2019, Tambe, Cappelli et al. 2019).

Early research on selection predominantly concentrates on evaluating the reliability and validity of organizations' selection methods and processes (Schmitt et al. 1984). As research on organizational practices expands, a new research direction emerges, emphasizing not only organizations' actions but also applicants' reactions, from both theoretical frameworks and empirical investigations (Nikolaou et al. 2019, Langer et al. 2020, Muralidhar et al. 2020, Folger et al. 2021, van Esch et al. 2021, Gonzalez et al. 2022, Kleinlogel, Schmid Mast et al. 2023, Oostrom et al. 2023). This line of research gains significance as it was theorized that applicants' responses to the selection process could influence a range of outcomes.

There are various reasons why companies should take special consideration of applicant perceptions of their selection procedures. For one, those perceptions can affect the applicants' attraction to the organization, job pursuit intentions, and impressions of the organization's justness (Schinkel, Vianen, & Dierendonck, 2013). All these factors play into a company's ability to competitively recruit and select top talent and initiate relationships with employees that foster a positive organizational culture (Smither, Millsap, Stoffey, & Pearlman, 1996). For example, research has demonstrated that there is a relationship between applicant reactions and applicant behavioral outcomes, such as referring a company to a friend (Bauer, Truxillo, Paronto, Weekley, & Campion, 2004).

This suggests that it is important that organizations are aware of applicants' reactions so that they can be better informed of the potential consequences of their selection procedures. The following sections provide a brief account of the research questions, the research design employed to address them, and the contributions that this research provides.

1.2 Problem Statement

Applications of AI in the R&S process are now attracting more and more attention from researchers (Rodney, Valaskova et al. 2019, Griswold et al. 2021, Langer et al. 2021, Mirowska and Mesnet 2021, Gonzalez, Liu et al. 2022, Kleinlogel, Schmid Mast et al. 2023, Meng 2023, Oostrom, Holtrop et al. 2023). AI-enabled recruitment has the potential to become the most impactful component of an organization's comprehensive talent competition and strategic HR management (van Esch et al. 2019). It offers convenient ways to screen and select applicants. Providers of digital interviews and companies applying these interviews promote them to be more time- and cost-efficient than Face-to-Face interviews (FTF).

More recent studies have focused on applicant reactions to AI-based interviews (Zusman and Landis 2002, Cober et al. 2003, Williamson et al. 2003, Cober et al. 2004, Sylva and Mol 2009). Blacksmith et al. (2016) conducted a meta-analysis and revealed that technology-enhanced interview methods are generally less favored by interviewees.

This discovery can serve as a foundation for research that explores the impact of emerging technologies on the interview process from the perspective of applicants.

Some researchers claimed that applicants have a positive perception of selection procedures performed by an AI. Job applicants are likely to perceive a selection process conducted by an AI as more satisfactory and more just than the same process conducted by a human. Human involvement in the recruitment process invariably introduces a degree of unconscious or conscious bias. Bias-driven decision-making is a pervasive issue in various organizations, and AI solutions serve to mitigate this factor. By relying solely on applicants' data and resumes, these solutions provide organizations the opportunity to hire based on true potential and fair judgments.

However, the research has also found negative impacts of AI-enabled interview methods in terms of applicant reactions, fairness perception, and interviewee performance ratings (Blacksmith, Willford, & Behrend, 2016; Chapman, Uggerslev, & Webster, 2003; Sears, Zhang, Wiesner, Hackett, & Yuan, 2013). For instance, videoconference interviews are perceived as less fair and offer less opportunity to perform than face-to-face interviews (Chapman et al., 2003; Sears et al., 2013). Furthermore, AI-enabled interview seems to evoke even less favorable reactions than videoconference interviews (Langer et al., 2019) because of lower social presence. The empirical findings on the overarching relationship between AI-enabled interviews and applicant reactions remain inconclusive.

The technological evolution of the interview continues. Currently, the use of highly automated interviews is burgeoning (Langer et al., 2019). Within such interviews, sensors (cameras, microphones) in combination with algorithms and virtual visualization automate the entire interview process (Langer et al., 2019). Scholars have asserted that theoretical research lags behind practical applications (Kleinlogel, Schmid Mast et al. 2023).

In summary, despite concerns about the impact on applicants, practical applications of this technology are advancing faster than theoretical research in the field. In addition, due to technological progress, high-speed internet, and anthropomorphic virtual characters, it is possible to create a conversation quality that can come close to FTF communication. Therefore, it is unclear to what degree these results hold nowadays. Moreover, the empirical findings on the overarching relationship between AI-enabled interviews and applicant reactions remain inconclusive.

1.3 Research Question

Building upon the aims of the research and the gaps presented in Section 1.2 mentioned above, the overarching research question guiding this study is **how applicants perceive and react to the AI-enabled interview.** This thesis looks to address three core research questions:

RQ1: How AI-enabled interview influence applicant reactions and behavior compared to a face-to-face interview?

RQ2: What factors contribute to applicants' reactions and job offer acceptance intention?

RQ3: How do different settings (strategies) of AI-enabled interviews influence applicants' perceived fairness and perceived social presence?

1.4 Thesis Structure

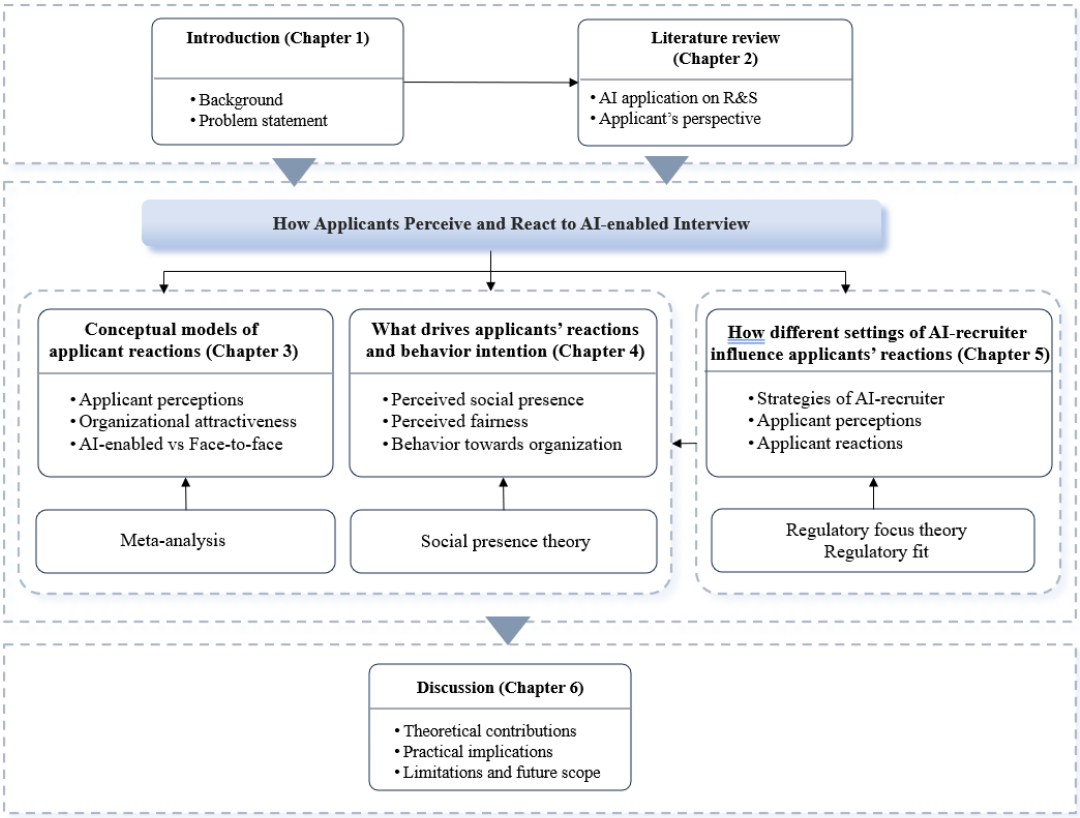

Figure 1.1 Thesis structure.

Figure 1.1 shows the structure of this research, the remainder of this study is organized as follows. Chapter 1 introduces the background of the study. In this chapter, the backdrop of the study is presented, offering an in-depth exploration of the previous context and fundamental principles that underpin the research.

Chapter 2 conducts an extensive review of the existing body of literature on the subject, analyzing and evaluating prior research to provide a comprehensive overview of the topic's background.

Chapter 3 conducts a meta-analysis for exploring potential job applicants' perceptions of AI-enabled interviews by having them compare their selection procedures with those conducted by a human recruiter. It delves into the intricacies of how applicants perceive and respond to AI-enabled interviews, exploring various factors that shape applicant and behavior intention.

Chapter 4 investigates the determining factors of job applicants' reactions and behavioral intentions by introducing the Potosky (2008) framework. This proposed framework generates ideas about potential differences between the interview formats (Langer et al. 2019, Langer, König et al. 2020, Langer et al. 2020, Langer, Baum et al. 2021, Roulin et al. 2022), and how these attributes influence the selection process dedicates to an in-depth examination of the factors that influence job applicants' reactions and their behavioral intentions during the AI-enabled interview process.

Chapter 5 is based on the regulatory focus theory. It is employed to gain insights into the intrinsic factors that underlie perceptions of AI-enabled interviews, offering an in-depth exploration of the psychological and cognitive aspects shaping applicant responses.

Chapter 6 discusses the findings, implications, and limitations of this study. This chapter serves as a platform for synthesizing the research findings, discussing implications, and acknowledging the study's limitations. This section provides a holistic perspective on the implications of AI-enabled interviews in the field of recruitment.

1.5 Research Philosophy

Research philosophy is about researchers' beliefs and assumptions (Bajpai 2011), which influence choices of research strategy, and the way researchers understand and conduct research (Johnson and Clark 2006). From this view, research philosophy is important to recognize when conducting research.

Ontology is the study of what entities exist. It is the nature of reality. In other words, it is about the nature of existence (Crotty 1998). Ontological stances facilitate how researchers study the research (Saunders et al. 2019). Objectivism and subjectivism are two kinds of perspectives. Objectivism describes reality exists independent of those who live it. Subjectivism perceives that reality is created in our minds (Bryman 2016). The main idea of my research is to study how applicants react and perceive the AI-enabled interview. Therefore, I define my ontological position as realism. It is often taken to imply objectivism.

The epistemology portrays assumptions about the way of getting knowledge (Burrell and Morgan 1979). Different academic disciplines and researchers adopt different epistemologies. Objectivists assert that knowledge is acquired through empirical analysis. However, subjectivism describes there is no reality but what people perceive it. Constructionism states the way we understand knowledge is constructed. I define my epistemological stance as objectivism.

Axiology refers to whether a personal value is involved during the research process. Researchers with value-bound are trying to explain the world. While researchers with value-free are trying to understand the world regardless of personal values(Lee and Lings 2008). For me, values are relevant. I take the middle. My research starts with my interests, the overall aim is to seek useful solutions to identify information at a low cost. The result can have a practical application. During the process of collecting and analyzing data, I will minimize the personal value to make the result generalizable. In 1962, Thomas Kuhn proposed the word paradigm in his book. He illustrated the word paradigm by using three different perspectives which are the philosophy of science, history of science and the society of science (Kuhn 2012). Every paradigm has its ontology, epistemology, axiology, and methodology. Researchers with different ontological and epistemological stances will adopt different methodologies when conducting research.

Therefore, being objective and minimizing bias are of importance (Schrag 1992). Positivism philosophy will guide the research. During the process of collecting and analyzing data, I will minimize the personal value to make the result generalizable. Overall, my research is aligned with positivism and pragmatism research philosophy. They can be a partner to guide my research. Meanwhile, it helps me select the appropriate methodology and meet the standards of scholarly rigor and thoroughness.

2 Literature Review

Many scholars have conducted in-depth research on R&S (Ployhart et al. 2017). The pivotal role of Information Technology (IT) in recruitment significantly influences all facets of an organization’s recruitment process. As Singh and Finn (2003) elucidated in their seminal work, IT affects individuals at all levels of the organizational level. It affects people due to changes in job demand and the number of applicants and reshapes processes.

Effective IT utilization often necessitates the adaptation of novel procedures and workflows. The primary intent behind the incorporation of IT in recruitment is the creation of new processes designed to reduce labor costs, enhance efficiency, streamline transactions, and provide superior services to stakeholders. Specifically, many recruiters find web-based pre-screening a cost-effective method for assessing the most suitable potential applicants for their positions (Applequist et al. 2020, Rodrigo et al. 2021). This relatively new process is more economical than hiring full-time HR consultants. Moreover, compared to conventional methods, online advertising costs are substantially lower (D'Silva 2020, Hosain et al. 2020). It is also a rapid, efficient, and timely recruitment method. One of the key ways through which information technology revolutionizes recruitment is by managing a high volume of job applications and numerous job vacancies.

The Internet, available 24 hours per day, permits the posting of job advertisements and the submission of job applications at any time and from any location. Snell et al. (2023) indicated that the final effect of these process changes is that human resources (HR) functional departments respond to stakeholders with greater alacrity, and no longer gain power by accessing and owning employee data. Due to these databases are available centrally, HR department has initiated the practice of sharing these databases throughout the organization. This development fortifies the organization’s foundation and structure, emphasizing collaboration and information sharing rather than mere data storage and pseudo-ownership.

As a result, the integration of IT into recruitment fosters collaboration and synchronicity within HR teams. Moreover, the development of specialized computer software for collaborative purposes enhances teamwork both within and outside the organization. Allal-Chérif et al. (2021) conducted a review of available technologies that are optimizing various stages of the recruitment process. In particular, with the widespread adoption of AI technology, there is growing interest in the role of AI in the R&S process (Woods et al. 2019). Hence, it is imperative to devote more scholarly attention to this topic (Iddekinge et al. 2013, Hmoud and Laszlo 2019, Hunkenschroer and Luetge 2022, Ore and Sposato 2022). This paper will focus on AI-enabled interviews, providing insights into existing research and studies in this field. However, so far, how technology affects the R&S process has not been well studied (Potonik et al. 2021).

2.1 AI application in the R&S process

In the summer of 1956, a group of visionary young scientists, led by McCarthy et al. (2006), gathered together to study and discuss a series of issues related to the use of machines to simulate intelligence. During this meeting, they introduced the term "artificial intelligence" for the very first time (McCarthy, Minsky et al. 2006). In the following decades, due to the rapid advancements in computer data storage and processing capabilities, AI concepts and technologies have undergone dynamic development and continual refinement and have been widely used in various fields. Today, AI stands as a burgeoning field within technology, dedicated to researching and developing theories, methodologies, technologies, and application systems that replicate, enhance, and extend human intelligence. It comprises a multitude of technologies, such as machine learning, natural language processing, and automatic programming, etc. (Russell 2010). In general, the objectives of AI research encompass learning, reasoning, and perception, so that computers and machines can tackle intricate tasks.

In recent years, AI is a burgeoning technology that has received increasing attention in both academia and industry. While AI is far from matching human cognitive abilities, it possesses fundamental functionalities, such as learning, complex decision-making, and critical thinking, which can be executed by advanced machines. AI-based software represents the most versatile solution for various organizational departments, offering enhanced opportunities for automation. These automated processes, devoid of the requirement for high creativity, are ideally suited for execution by AI-driven machines.

The development of AI technology is progressing rapidly and is swiftly becoming an integral part of our daily lives. This burgeoning technology is reshaping every facet of people’s lives. It is now widely employed in various domains, including automatic driving, natural language comprehension, automatic speech recognition, automated stock trading, etc.

Moreover, it has penetrated the HR department by providing invaluable support to HR leaders in crafting strategic talent strategies and achieving outcomes. AI can also revolutionize the way HR managers view, select, and operate applicants screening. AI-recruiter is the application of AI in various recruitment functions, including learning or problem-solving those computers can perform. This emerging technology aims to simplify or automate some parts of the recruitment workflow, particularly repetitive and high-volume tasks. It opens the door to automating low-level tasks, and more sufficient information can immediately reduce operating costs.

R&S, as key steps of human capital, play a vital role in the construction and management of human resources of the whole enterprise. R&S are the ways for enterprises to obtain human resources. On the other hand, it means selecting the most suitable employees to match individuals with positions, individuals with teams, and individuals with organizations. The impact of recruitment quality on enterprises is often long-term, even decisive. Therefore, the company is constantly committed to simplifying the human resources process with the help of new technologies.

R&S are important and continuous activities, which are directly related to the company's development in the market. "Recruitment is the process of attracting and encouraging potential employees to apply for positions, while selection is the process of conducting a fair and relevant evaluation of the advantages and disadvantages of applicants and planning to hire them" (Sutherland and Wöcke 2011).

Recruitment is the process of actively looking for and hiring the best applicants for specific positions or job roles. It refers to the formulation of corresponding vacancy plans and recruitment of appropriate personnel by enterprises according to the guidance of the overall development plan. This is not a short-term process. It involves many steps, from job advertisement to the use of different software to the determination of applicants' lists, and finally, according to the company's requirements, screening, and interviewing applicants meeting the predetermined criteria. When the most suitable applicants are determined, they will be recruited and integrated into the workplace, and the recruitment process is over.

Singh and Finn (2003) discussed that the recruitment process, as the entry point for employees, plays a vital role in improving the survival and success of organizations in the highly competitive and volatile business ecosystem. Accordingly, Heraty and Morley (1998) pointed out that the most critical structural challenge at the organizational level today is to recruit the most qualified individuals, while still meeting the regular job requirements. It is important to understand the decisions made at the early stage of recruitment, as this will affect the overall strategic long-term vision of the organization (Henderson 2017). As Sangeetha (2010) said, the R&S process is the key to how an enterprise views human resources, which is crucial to maintain its competitive advantage over its competitors. To gain a competitive advantage, every step of the R&S process should be carefully considered, because wrong decisions in recruitment may have a negative impact on the entire organization. Carter (2015) believed that inappropriate employees would consume time, affect team morale, and possibly damage customer relations and organizational culture.

In detail, AI assists recruiters complete a unified file from many unstructured datasets, effectively matching the requisite skill sets for a position with an applicant's work history. For instance, AI can play a pivotal role in supporting interviewers during the R&S process. Employing AI in interviews is advantageous, as AI interviewers remain impervious to emotional biases stemming from personal, psychological, or physical attributes and other external conditions that human interviewers may be influenced by.

AI's commitment to improving employment quality lies in its ability to use data to standardize the match between applicants' experience, knowledge and skills, and job requirements. The advantages of AI adoption are manifold, recruiters are relieved from the arduous task of sifting through crowded job markets and endless applicants' lists. This makes the HR process very simple and fast. The background has transformed AI-enabled recruitment from a desirable feature to an indispensable necessity in the HR department. In conclusion, AI-enabled recruitment tools are predominantly applied in three broad categories of activities: outreach, screening, and assessment (van Esch, Black et al. 2021).

Outreach

In the outreach phase, organizations aim to identify potential applicants and present job opportunities in a manner that encourages them to apply (Guinan et al. 2014). That is to say, the aim of outreaching is finding and connecting with talent quickly. Due to the importance of identifying the most suitable talent, companies' outreach efforts not only need to be as broad as possible, but also targeted. Organizations aspire to reach as many pertinent active applicants as possible. However, most potential applicants fall into the category of passive applicants, as they are not actively seeking new employment opportunities. According to Smith and Kidder (2010), it's surprising to note that almost 80% of individuals who are not actively involved in job hunting would still be receptive to the idea of considering a suitable job opportunity if it were presented to them. A recent report from Harvard Business School found that top candidates are becoming more "hidden" to recruiters than ever before. It's worth emphasizing that the number of passive candidates significantly surpasses that of active candidates, estimated to be approximately three times greater. Ultimately, therefore, the challenge for hiring managers is to ensure well-qualified candidates seeking employment are included in the recruitment process. This is also the main goal of the outreach phase.

The ideal candidate pool for organizations comprises a combination of both active and passive job candidates. Guinan, Parise et al. (2014) presented that it is of importance for organizations to employ intelligent methods identifying both active and passive job candidates to construct the best candidate pool. Several companies, including Pandologic, Talenya, and HireScore, employ AI to extract data from various social platforms such as LinkedIn, Facebook, Instagram, Pinterest, Twitter, XING, Ryze, Beyond, and MeetUp (Campbell et al. 2020). Subsequently, AI systems are used to align these candidates with job positions. Indeed, companies like Pandologic, and HireScore leveraging the power of AI to extract data from various social platforms, including LinkedIn, Facebook, Twitter, Instagram, etc. Subsequently, this data is employed to effectively diversify the applicant pool (Campbell, Sands et al. 2020).

AI can not only assist organizations in expanding their applicant pool but also in precisely targeting more suitable talents. For instance, Unilever collaborated with

Pymetrics, an AI-enabled recruitment solution provider, to identify qualified applicants for its 200 crucial internships. The application of AI-enabled recruitment has led to a remarkable increase, with the number of applications more than doubling from 15,000 to 30,000 (Feloni 2017). In other words, there were 150 applicants for each available position. Additionally, this technology has significantly bolstered the diversity of the applicant pool. Furthermore, Unilever reported an expansion in its applicant base, increasing from 840 universities to 2,600 universities. Even more remarkably, in 2017, L'Oréal employed AI not only to reach active applicants but also to identify passive applicants. The outcome was astonishing, with L'Oréal receiving 2 million resumes for just 5,000 positions, equating to an incredible 400 applicants for each position (Sharma 2018).

Except for targeting accurate job advertisements, AI technology can also extend to improve wording in job advertisements Over time, as the algorithm continues to learn and train with data, AI tools will adapt which methods are most effective for specific applicant types. More precisely, AI is designed to pinpoint the ideal talent and tailor its job advertising and text content to suit them. The system accurately pushes job opportunities via banners, pop-up windows, emails with the aim of not only attracting applicants effectively but also eliciting prompt responses. For instance, Textio, a recruiting software, helps hire and retain a diverse team. They employed AI to refine the words used in job advertisements and monitored the changes of these adjustments on both the volume of applicants and the various demographic characteristics. This approach assists clients in enhancing the impact of their outreach efforts. Johnson & Johnson adopted Textio to tailor its job advertisements, leading to a remarkable 13% increase in the recruitment of qualified female employees (McIlvaine 2023). Similarly, L'Oréal employed AI to eliminate gender-biased language, ultimately achieving an equal representation of male and female applicants, which is a milestone the organization had never achieved (Sharma 2018).

With the advent of the big data era, not only has the scope or scale of the talent pool expanded significantly, but the depth of applicants' information. In 2018, LinkedIn had nearly 600 million users, each of whom maintained hundreds of data points within their profiles. Even with the organization employing a substantial workforce, the task of intelligently and efficiently sifting through an enormous volume of profiles would be impossible without the assistance of AI.

These examples vividly demonstrate how AI has pushed the boundaries of the reach-richness frontier even further. Through the application of AI, companies can now not only engage with thousands of active applicants for a specific position but also target more passive applicants. It not only broadens the applicant pool but also enhances the diversity of applicants. Moreover, after identifying active and passive applicants, AI has the potential to identify which facets of the company (culture, values, mission, technology, etc.) should be highlighted when presenting opportunities to applicants leading to the most positive responses (Kakatkar et al. 2020).

Screening

In the screening phase, AI is employed to sort through resumes and applications and advance the best applicants to the next stage of the recruitment process. In essence, the objective of screening is to efficiently identify the most qualified applicants. AI-enabled screening ranges from resume parsing to behavioral and skill assessments. Resume screening tools leverage machine learning algorithms to analyze the content within PDF or Word files. In practice, the applicant uploads their resume into the parsing tool. Subsequently, AI scans each document and extracts information aligned with job requirements, including applicants' skills, experience, qualifications, etc. The processes are aimed at streamlining the time-consuming process of sifting through resumes to find well-qualified applicants.

The evidence supporting the time-saving benefits of AI-enabled screening deserves attention. For example, Ideal, an AI-enabled screening tools provider, asserts that among its clients, the time-to-hire has significantly decreased from an average of 24 days to just 9 days, marking a remarkable 62.5% reduction. Hilton Hotels & Resorts adopted an AI-enabled screening and observed a substantial reduction in time-to-hire, from 42 days to a mere 5 days, signifying an 88% decline (McLaren 2018). Moreover, L'Oréal employed AI-enabled screening tools, resulting in a substantial reduction in resume review time. The duration to review a resume decreased dramatically from 40 minutes to just 4 minutes, marking a remarkable 90% reduction (Sharma 2018).

Although further research and in-depth studies are required to comprehensively determine the impact of AI on time-to-hire, the evidence from specific company case studies strongly suggests that AI has the potential to yield substantial reductions in the hiring lead time. Although further research and in-depth studies are required to definitively establish the impact of AI on time-to-hire, specific case studies from industries strongly indicate that AI has the potential to lead to substantial reductions in the process of screening resumes.

The reduction of time-to-hire enhances an organization's potential strategic advantage in the war of human capital. Consider the case of Hilton, as mentioned earlier. According to the U.S. Bureau of Labor Statistics (Indexes 2014), the annual turnover rate for hotels surpasses 70%. In this context, hotel companies like Hilton are continuously engaged in recruiting staff.

If we assume that Hilton can extend an offer to a housekeeping job applicant in just 5 days, while its competitor takes 40 days, Hilton will likely prevail in securing those housekeeping applicants and win the competition of talents. Indeed, it is unlikely that applicants would wait for 40 days after receiving an offer from Hilton to ascertain if they would also receive an offer from a competitor. In such a scenario, Hilton's prompt offer would likely result in the applicant accepting their job offer without hesitation. Therefore, the capability of AI to reduce time-to-hire signifies not only an enhancement in efficiency but also potentially a crucial strategic advantage in the competition for human capital, particularly in industries characterized by high turnover rates.

In addition to the anticipated enhancements in recruiting speed and efficiency facilitated by AI, there are also substantial prospects for effectiveness. Kuncel et al. (2014) reveal that AI-enabled tools exhibited at least a 25% advantage over humans in screening applicants, even when humans dedicated a reasonable amount of time to evaluating applications or resumes. Presently, AI-enabled screening has advanced beyond the mere identification of keywords in applications and resumes. It can infer capabilities of applicants that may not be explicitly mentioned in the text. For instance, a specific job may necessitate the attribute of "persistence". Instead of solely searching for that term or its common synonyms. AI-enabled screening tools can infer the attribute of persistence from natural language sentences that describe not giving up when confronted with obstacles or persevering in overcoming resistance when implementing new processes.

Assessing

AI-enabled assessing typically involves machine-learning algorithms that analyze your submissions and provide insights to help hiring managers make more informed decisions (Meijerink et al. 2021, Ore and Sposato 2022, Rodgers et al. 2023). The main applications of AI-enabled assessments are game-based assessments and AI-enabled interviews. Once companies have completed the screening, eliminating a substantial portion, often ranging from 50% to 80%, AI-enabled assessments can further narrow the number of applicants. These assessments can take various forms, including gamified tests, also called game-based assessments that offer insights into an applicant's skills, capabilities, and even personality. Their accuracy is like, and in many instances, even higher than that of longer and more repetitive psychometric tests.

The case of game-based assessment deserves much more attention. The Dutch-British consumer-goods giant Unilever has been using game-based assessment to measure inherent traits (Feloni 2017). In detail, applicants spent about 20 minutes playing 12 neuroscience-based games on the Pymetrics platform. The was designed to assess risk-taking behavior. In this game, applicants had a time limit of 3 minutes to accumulate as much money as possible by clicking the 'pump' button to inflate a digital balloon filled with both air and money. Each click contributed 5 cents. Importantly, at any moment, applicants had the choice to cash out their earnings, add the accumulated amount to their overall score, and initiate a new balloon. However, if they waited too long and the balloon burst, they would receive no money from that balloon. The game's objective was not solely to measure the amount of money collected but to gauge an individual's propensity for risk-taking.

Obviously, before integrating game-based assessment into their recruitment process. Unilever needed to have a deep understanding of the connection between risk propensity and job success, particularly for specific roles such as product managers. Unilever uncovered an inverted ‘U’ relationship between risk propensity and job performance. More specifically, they observed that moderate and moderately high levels of risk propensity exhibited positive correlations with job performance. Conversely, both low and very high levels of risk propensity had negative associations with job performance.

Not only the game-based assessment but also the AI-enabled interview has transformed the hiring process. AI-enabled interviews represent an automated procedure that leverages machine learning algorithms to evaluate job applicants. It identifies qualified applicants by analyzing data including facial expressions, tone of voice, and body language, which yield valuable insights into an applicant’s personality and suitability for the role.

HireVue (HireVue 2018), an AI-powered interview provider, due to the technology advancement, is gaining popularity as a hiring tool among major banks and accounting firms, including J.P. Morgan, Goldman Sachs, Morgan Stanley, and Deloitte. The HireVue website lists notable clients such as T-Mobile, Cathay Pacific, and Unilever among hundreds of other companies. The HireVue website even states Urban Outfitters, Singapore Airlines, and Intel as clients, among hundreds of other companies. In detail, interviews don’t interact with a real human during the AI-enabled interview. Instead, they receive a series of interview questions that you answer via video on your laptop, tablet, or smartphone. They typically get 30 seconds to prepare before you have a set time, ranging from 90 seconds to three minutes (depending on the question), to record and submit your response. Furthermore, HireVue transcribes the responses and assigns the interview a score, which is utilized to rank among the other applicants. It’s important to note that AI doesn’t just evaluate the content of your spoken words. It also assesses the facial expressions, eye contact, gestures, voice intonation, and numerous other data points extracted from the video or interaction.

L'Oréal also employed an AI-enabled interview tool from Mya Systems to evaluate applicants who had successfully passed the initial screening process. Mya, an AI chatbot, interactively presented interviewers with three questions (Sharma 2018): The first question is to describe a project you were involved. What did you learn from this experience? The second question is to share an instance where you collaborated with multicultural teams. The third question is to narrate a situation where you believed in your idea, but your superiors were not. How did you manage to persuade them? The AI system then proceeded to analyze and compare the responses provided by applicants with those given by high-achieving L'Oréal employees. This analysis encompassed an assessment of sentence structure and vocabulary used in the responses. By combining the content analysis with these linguistic factors, the system generated an overall score for each applicant.

In conclusion, according to the discussion mentioned above, this paper summarized the overall AI application framework combined with the specific dimension of the R&S process. Figure 2.1 shows the framework of AI-enabled interviews.

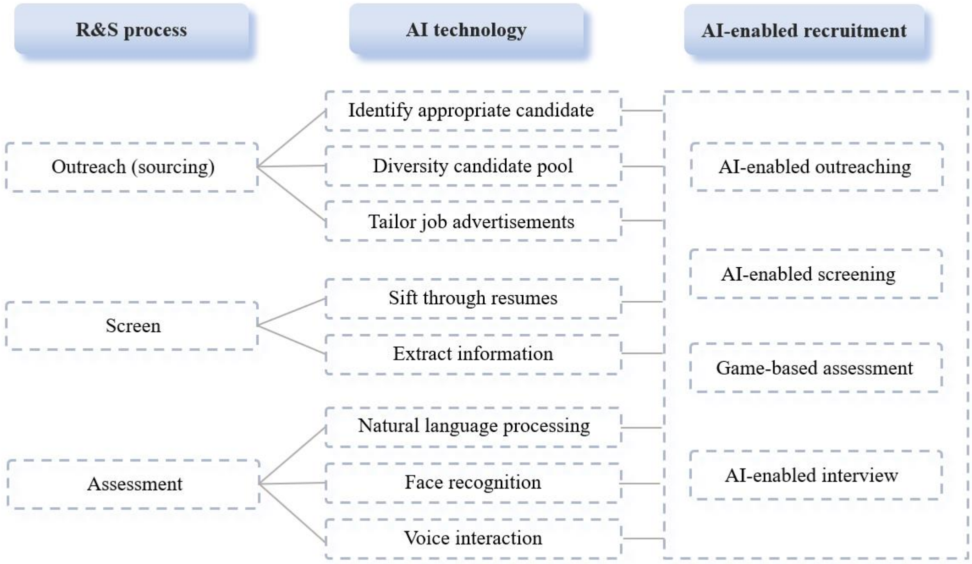

Figure 2.1 Framework of AI-enabled interview.

2.1.1 Advantages of AI Application in R&S Process

AI-enabled recruitment plays a vital role in streamlining the recruitment process. AI tools alleviate the workload associated with arduous and time-consuming repetitive tasks, such as applicant sourcing, screening, etc. These advantages will significantly contribute to cost savings in recruitment and enhance the overall quality of the R&S process. Moreover, AI will enhance the transparency of the recruitment process by mitigating human bias, leading to an improved perception of employers by job seekers. This, in turn, bolsters the image and reputation of employers. Given all these potential advantages, there is no doubt that the prevalence of AI involvement in the R&S process will continue to grow soon. The following are the benefits of AI in the R&S process (Rathi 2018, Yawalkar 2019, Ore and Sposato 2022):

Benefit 1: Improve recruitment quality. The recruiter faces the task of sifting through a substantial pool of applicants to find the most suitable applicants. The AI-enabled recruitment process can be structured into multiple rounds, enabling recruiters to gather more comprehensive data for each applicant, thus facilitating more effective applicant evaluation.

Benefit 2: Better integrated analysis. Recruiters can now align applicants with specific job requirements, identifying positions that are in most need of an individual's skills and abilities. This innovative approach not only enhances organizational productivity but also motivates applicants to refine their skill sets. Furthermore, AI-enabled screening software outperforms human recruiters in terms of efficiency.

Benefit 3: Automation saves time. Time is a valuable resource for every organization, and the recruitment industry is no exception. AI offers a range of solutions for skill evaluation. AI-based software can rapidly analyze extensive applicant data, generating easily comprehensible results that are invaluable to recruiters. This time-saving aspect not only conserves time but also contributes to cost and resource savings for organizations.

Benefit 4: Unbiased decision-making. Human involvement in the recruitment process invariably introduces a degree of unconscious or conscious bias. Bias-driven decision-making is a pervasive issue in various organizations, and AI solutions serve to mitigate this factor. By relying solely on applicants' data and resumes, these solutions provide organizations the opportunity to hire based on true potential and fair judgments.

A study conducted by Rodney, Valaskova et al. (2019) revealed the significant role of AI in the R&S process. AI-enabled recruitment has the potential to become the most impactful component of an organization's comprehensive talent competition and strategic HR management (van Esch and Black 2019, van Esch, Black et al. 2019). AI can simplify labor output by processing reduced value-added or auxiliary tasks (Ionescu et al. 2013, Vasile et al. 2016, Popescu et al. 2019), which makes it possible for workers to handle high-value jobs and can promote companies to improve currency utilization, as found by Plastino and Purdy (2018). Moreover, they emphasized that, given the exponential growth of information, the increasing affordability and expansion of computing power, and the continual advancement of technology, AI is being recognized as a productivity enhancer and multiplier.

2.1.2 Risks of Using AI in the Recruitment Process

During the whole recruitment process, the company can collect supplementary data, such as age, health status, body image, race, gender, sexual orientation, and economic class, and use these data to systematize the job seekers to a greater extent and differentiate in job screening when feasible. Extracting additional information can also lead to ethical and privacy issues (van Esch, Black et al. 2019).

Hunkenschroer and Luetge (2022) conducted a comprehensive review of the ethical aspects of AI-based R&S. Their discussion centered on ethical dilemmas and offered recommendations for alleviating ethical risks. Scholz (2017) sounded a warning about AI-enabled recruitment, emphasizing the ethical issues surrounding fairness and discrimination, specifically the potential for alienating prospective applicants. This ethical concern regarding fairness and discrimination has been a consistent criticism in practice. This concern stems from the fact that AI tools, including machine learning, rely on algorithms to generate recruitment predictions. Nevertheless, bias could be introduced through the training data employed in algorithm models (Eubanks 2022).

Hurlburt (2017) argued for a closer examination of the issue of trust, particularly due to significant apprehensions about bias in AI. Hurlburt investigated the potential for coders to involve their cultural or personal biases intentionally or inadvertently in AI algorithms. Specifically, it is important to highlight that Cappelli (2001) concluded that technology has the potential to " reject a disproportionate number of underrepresented groups, including women, minority ethnics, disabled people, and workers older than forty years of age." As Fernández and Fernández (2019) and (Eubanks 2022) indicated, the potential for employment discrimination in AI-enabled recruitment gives rise to ethical dilemmas, whether intended or unintended. Such dilemmas could result in substantial brand damage and discriminatory recruitment practices. There is growing evidence indicating that AI algorithms can cause discriminatory behavior, even when the computational process is fair and well-intentioned. This discrimination often arises due to bias or non-representative learning data in combination with unintentional modeling procedures (Žliobaitė and Custers 2016).

2.1.3 AI-enabled Interview

Technology is extensively employed to enhance the efficiency of job interviews, ranging from getting initial impressions of applicants to conducting interviews (Bauer et al. 2004). Over the years, technology has been used in various ways for job interviews. Specifically, as for telephone interviews, a representative from the organization presents interview questions to applicants via the phone. This implies the establishment of a communication channel primarily relying on verbal interactions. In videoconference interviews, the interviewer and interviewee can hear and see each other through camera technology. However, these technology-mediated interview approaches appear rather old-fashioned (Langer, König et al. 2020).

Increasingly, AI defined as machines capable of performing tasks requiring human intelligence (Luger 2008), is progressively used to interview and evaluate job applicants. In a standard AI-enabled interview, job applicants communicate through their computer cameras, and the AI platform gathers and assesses their responses, including verbal and nonverbal elements, such as facial movements. These evaluations are used to rate the applicants' employability and make informed decisions (Harwell 2019). Many organizations have already incorporated AI-enabled interview systems into their R&S processes (Jaser et al. 2022). For instance, the German company Precire automatically assesses applicants' voice recordings (Precire 2018), while the American company HireVue (HireVue 2018) also evaluates applicants' nonverbal behavior, such as smiling. Initial efforts have been made to employ virtual characters as interviewers to enhance the human touch in AI-enabled interviews (Lee and Nass 2003, Langer, König et al. 2018).

While the basic form of AI-enabled interview shares similarities with video-conference interviews and other technology-mediated interviews, it holds the potential to provide significantly more flexibility, standardization, and analytical capabilities when compared to telephone or videoconference interviews. In other words, it doesn't need scheduling and is influenced by human emotions. As a result, it was reported that organizations are displaying a keen interest in this form of interview, and AI-enabled interviews are widely regarded as one of the emerging trends in personnel selection practice (Brenner et al. 2016, Chamorro-Premuzic et al. 2016, Schmerling 2017). A web search for AI-enabled interview providers yields over 70 companies offering solutions (Advice 2017).

In a traditional hiring process, the recruitment team screens job applicants' resumes, conducts interviews, either remotely or onsite, assesses their performance, evaluates their suitability for a specific role, and then finally decides whether an offer should be extended. In such instances, the decision-making authority remains entirely with the human recruiters. Conversely, in AI-enabled interviews, although human recruiters can still exercise some decision-making agency through designing interview questions or setting certain parameters, they neither base their decisions on their perceptions of an applicant nor establish explicit rules for the AI system to follow (Naim et al. 2016, Langer, König et al. 2019). Mittelstadt et al. (2016) reported AI system employed machine learning algorithms to define or modify decision-making rules autonomously (Adepu et al. 2020). Liu (2021) pointed the rules of AI's decision-making are largely data-driven, not predetermined by humans. As such, it is also called a black box for both applicants and recruiters. Therefore, during the AI-enabled interview process, the agency of decision-making in recruitment shifts from humans to machines. Table 2.1 illustrates the distinctions between human-AI interaction (HAII) and an AI-enabled interviewer across six dimensions.

Table 2.1 The distinctions between HAII and an AI-enabled interview.

	HAII	AI-enabled Interviewer
Examples	Autonomous vehicle intelligent decision system	Tengai HreVue
Role of machine	Teammate of human	Supervisor (Kim and Mutlu 2014)
Role of human	Teammates cooperating with AI (humans should be the final decision maker).	Subordinate (Kim and Mutlu 2014)
User interface	Various of interactions, including graphical user interface (GUI), voice interaction, face recognition,	Mainly voice interaction and face recognition (Langer, König et al. 2020, Langer, König et al. 2020)

	brain-computer interface, etc.	
Behavior	Can be initiated by a human or machine	Initiated by machine.
Interpretability of system output	Many public algorithms and training data. Possible to reverse engineer some AI-systems (Hemmer et al. 2021, Sreedharan et al. 2021)	Total "black box" for job applicants

2.2 Applicant's perspective on AI-enabled Interview and applicant reaction

Langer and Landers (2021) pointed out there are three parties that should be considered in the context of AI-enabled interviews. The first party refers to people using or interacting with the output of AI-enabled systems. The second party is applicants who are directly affected by AI-enabled interviews. Third-party refers to people who could become a second party in the future, or concern some characteristic (e.g., privacy, transparency) of second parties.

Over the past two decades, the significance of human capital has escalated, with intangible assets surpassing tangible assets as the primary contributors to firm value (Hand 2002, Hand and Lev 2003, Becker et al. 2009, Black 2019). The increasing significance of human capital is primarily attributable to the fact that people are either at the core of or serve as the primary catalyst for, nearly all intangible assets (Hand 2002, Bhattacharya and Wright 2005, Becker, Huselid et al. 2009, Black and van Esch 2020). Consequently, the significance of human capital has underscored the value of efficiently recruiting, selecting, hiring, and retaining individuals (Hand 2002, Black and van Esch 2020). From a practical perspective, organizations must initially recruit and select their desired applicant before they can hire, onboard, or optimize their performance. Recruitment involves defining the applicant pool, attracting potential applicants, and motivating them to apply for open positions (Breaugh 2008). From the pool of applicants who apply, the selection process primarily focuses on evaluating and interviewing the individuals (Farr and Tippins 2013). Previous research on selection predominantly concentrated on evaluating the reliability and validity of organizations' selection methods and processes (Schmitt, Gooding et al. 1984).

As the research on organizational practices expanded, a new research direction emerged, emphasizing not only organizations' actions but also applicants' reactions, from theoretical frameworks and empirical investigations (Nikolaou, Georgiou et al. 2019). This line of research gained significance as it was theorized that applicants' responses to the selection process could influence various outcomes. These outcomes include their willingness to accept employment offers and subsequent post-hire work-related attitudes and behaviors, such as job satisfaction, organizational commitment, well-being, job performance, and turnover (Hausknecht et al. 2004, Athota et al. 2020).

Despite this heavy focus on applicants' reactions to selection, from a practical standpoint, one could make the case that understanding applicants' reactions to recruiting was equally, if not more, important. This is because applicants' reactions to recruiting directly impact the prerequisite outcome relative to selection—i.e., the decision by applicants to engage in and complete the job application process. After all, an applicant must apply for a job before the selection process can begin.

Interestingly, even though recruiting and selection are closely related in practice, the theories that have guided empirical research on these two topics have exhibited significant differences. As for the topic of applicant reactions to interviews, the dominant theoretical framework is organizational justice (Hausknecht, Day et al. 2004). Considering that, in the case of interviews, applicants are directly affected by salient organizational decisions. It is reasonable to expect applicants to question the fairness of the interview process (procedural justice) and its outcomes (distributive justice) (Hausknecht, Day et al. 2004). Therefore, organizational justice serves as a central theoretical guide (Folger and Greenberg 1985).

More recent studies have focused on applicant reactions to AI-based interviews (Zusman and Landis 2002, Cober, Brown et al. 2003, Williamson, Lepak et al. 2003, Cober, Brown et al. 2004, Sylva and Mol 2009). This research is particularly relevant considering the substantial growth in AI-based assessment since 2010 (Freeman 2002). The investigation of applicants' reactions to this specific technology is imminent. According to a recent survey, 39% of companies used AI-enabled tools in the selection of applicants (Oracle). Perhaps more importantly, this same survey that found the number of companies that plan to use AI-enabled tools in recruiting over the next two years will double (increasing from 39 to 79%). Considering the significance of applicant reactions to the selection process, the limited number of empirical studies on this topic (van Esch, Black et al. 2019), and the growing utilization of AI-enabled tools in interviews, it appears that the study on applicant reactions to AI-enabled interview could provide valuable insights for both research and practical applications (van Esch, Black et al. 2019).

2.3 Summarize and Thesis Structure

As this early stream of research on organizational actions grew, a new line of research emerged in which both the theoretical frameworks and empirical studies focused, not just on organizations' actions, but on applicants' reactions (Langer et al. 2017, Nikolaou, Georgiou et al. 2019, Langer, König et al. 2020). Most of this research focused on applicants' reactions to selection rather than recruiting. This line of research was seen as important because applicants' reactions to selection were hypothesized to affect a variety of outcomes, including candidate performance on selection assessments (e.g., cognitive tests, work samples, interviews), applicants' acceptance of employment offers, and various post-hire work attitudes and behaviors (e.g., job satisfaction, organizational commitment, well-being, resilience, job performance, turnover, see Hausknecht, Day et al. (2004) for a meta-analytic review (Athota, Budhwar et al. 2020).

While there has been growing research focus on applicants' general reactions to employee selection procedures in recent decades (Gilliland 1993, Ryan and Ployhart 2000, Hausknecht, Day et al. 2004, Chapman et al. 2005, Celani et al. 2008, McCarthy et al. 2017), there is a notable scarcity of research on how applicants perceive the use of algorithms in the hiring process (Dineen et al. 2004, Lee 2018, Kaibel et al. 2019).

So far, research has examined individuals' reactions to AI-based interviews relative to human-based interviews mostly with vignette-based designs, where participants saw a textual description of AI-based hiring procedures (e.g., Gonzalez, Liu et al. (2022), Köchling et al. (2022), Mirowska and Mesnet (2021), Schick and Fischer (2021)) and were asked to imagine how they would feel in such situations. Nevertheless, little research had participants go through the interview process to examine their experience. As individuals' operant psychological processes during real-time interaction with AI may differ from those reported in imaginative settings.

3 A Meta-analysis of Applicant Reactions to AI-enabled Interview

3.1 Introduction

Due to their greater speed and efficiency than traditional screening and assessment practices (van Esch and Black 2019), AI advanced selection tools are attractive to organizations and are considered valuable assets in today's "war for talent" (Leicht-Deobald et al. 2019). Today's trend toward more remote and home-based work has further prompted the adoption of alternatives to face-to-face interviews to evaluate applicants remotely.

To reduce operational expenses, access a broader global labor pool, and embrace environmentally sustainable approaches, organizations frequently employ various remote communication methods, such as telephone calls, video conferencing, or online chats, for conducting employment interviews (Andrews et al. 2013). In recent years, there have been significant changes in the format of job interviews. The technology-enhanced interview has been developed from telephone interviews to videoconference interviews, and now AI-enabled interviews (i.e., acquire information about applicants, evaluate applicants' performance, implement actions such as automatic selection of follow-up questions, using virtual interviewers) (Köchling, Wehner et al. 2022, Kleinlogel, Schmid Mast et al. 2023, Roulin et al. 2023).

Some researchers claim that potential job applicants are likely to perceive a selection process conducted by an AI as more satisfactory and more justice than the same process conducted by a human (Langer, König et al. 2018, Figueroa-Armijos et al. 2022). Since it minimizes human bias in the hiring process. By relying on algorithms and data-driven assessments, they reduce subjective judgments based on personal biases, ensuring fairer evaluations of applicants. While the issue of algorithmic bias in hiring decisions has attracted widespread interest among researchers, particularly from legal and technical perspectives, there are many more issues with AI hiring, such as data privacy, transparency, and accountability, that deserve discussion.

Although research on AI recruitment has increased significantly in recent years, there is still a lack of comprehensive understanding of recruitment as a context for the expanding application of AI. Blacksmith, Willford et al. (2016) conducted a meta-analysis and revealed that technology-enhanced interview methods are generally less favored by interviewees. This discovery can serve as a foundation for research that explores the impact of emerging technologies on the interview process from the perspective of applicants. However, the primary meta-studies were all conducted at least 8 years before the meta-analysis at a time when interview technologies were still facing problems, such as slow internet connections. Due to technological progress, high-speed internet, and anthropomorphic virtual characters, it is possible to create a conversation quality that can come close to FTF communication. Therefore, it is unclear to what degree these results hold nowadays. Hence, it is imperative for research concerning AI-enabled interviews to extend beyond these initial findings.

To fill this gap and lay a common foundation for future research in this area, it is critical to integrate existing theoretical and empirical methods to assess applicant reactions to AI recruitment. the primary objective of this article is to undertake a comprehensive analysis of the systematic understanding of how technology influences applicant reactions and behavior. Thus, the research question of this paper is as follows:

RQ: How an AI-enabled interview influence applicant reactions and behavior compared to a face-to-face interview?

The remainder of this chapter is organized as follows. Section 3.2 introduces the literature review and conceptualization of various terms followed by the research methodology description in Section 3.3. Results are shown in Section 3.4. Section 3.5 discusses the findings, implications, and limitations of this study.

3.2 Literature Review

3.2.1 Overview of AI-enabled Interview

Recruitment is the process of actively looking for and hiring applicants for specific positions or job roles. It involves many steps, from job advertisement to the use of different software.

We define AI recruitment as any process that utilizes artificial intelligence to assist an organization during the R&S of job applicants (Hunkenschroer and Luetge 2022), while AI can be defined as "a system that can correctly interpret external data and learn from that data, and the ability to use these learnings to achieve specific goals and tasks through flexible adaptation" (Kaplan and Haenlein 2019). We therefore refer to a broad concept of AI that includes complex machine learning methods such as deep neural networks, but also simple algorithms that rely on regression analysis as well as other types of algorithms such as natural language processing or speech recognition.

There are two main aspects that differ between FTF interview and AI-enabled interviews: the decision agent and the object of communication during the interview. Decisions in modern HRM procedures might not necessarily be made by humans (Ötting and Maier 2018, Langer, König et al. 2019, Langer, König et al. 2020, Langer, König et al. 2020, Roulin, Wong et al. 2022). In the case of AI-enabled interviews, the interview tool might independently decide how to react to a given interviewee. It identifies qualified applicants by analyzing data including facial expressions, tone of voice, and body language, which yield valuable insights into an applicant's personality and suitability for the role. In such cases, the AI tool is the decision agent. In face-to-face interviews, however, the decision agent is a human interviewer. In addition to the agent of communication, the interviewer of the AI-enabled interview is a virtual character. In other words, the interviewee communicates with a virtual character instead of a human.

As a result, organizations have exhibited significant interest in this form of interview, and AI-enabled interview is described as one of the rising stars in the R&S process (Brenner, Ortner et al. 2016, Chamorro-Premuzic, Winsborough et al. 2016, Schmerling 2017). In this study, FTF interview and AI-enabled interview are specified as antecedent variables. They are anticipated to impact behaviors (outcomes), mediated by applicant perceptions.

3.2.2 The Stimulus-Organism-Response Framework

Stimulus-organism-response (SOR) framework, introduced by Mehrabian and Russell (1974), is a robust analytical framework that effectively captures applicants' reactions to novel AI-enabled interviews. Its origins trace back to the seminal work of Mehrabian and Russell (1974), which laid the groundwork for extensive research on the influence of factors on individual behavior (Kaltcheva and Weitz, 2006). Since then, the framework has been used to understand human behaviors(Shah et al. 2020). Due to its utility and versatility, the SOR framework is widely used in information systems research. The SOR framework comprises three key elements. Stimulus refers to the environmental factor (Song et al. 2021). The organism is associated with an individual's affective and cognitive state. It mediates the effect between stimulus and responses (Wu and Li 2018). Based on the SOR framework, the proposed research model integrates applicant perception and their primary outcomes and behavior intention (Figure 3.1). As can be seen, important outcomes can be best predicted by applicant perceptions of the interview process. These outcomes include attitudes toward the organization and a variety of behavioral intentions. Applicant perceptions consider various dimensions of organizational justice, thoughts, and feelings about interviewing, perceived social presence, and perceived fairness. The model also specifies two antecedent variables, that is the type of the interview. Two classes of the interview are proposed as determinants of applicant perceptions. Each element of the model is discussed below accompanied by an empirical test. Therefore, applicant perceptions are reviewed first, followed by perception and outcome, respectively.

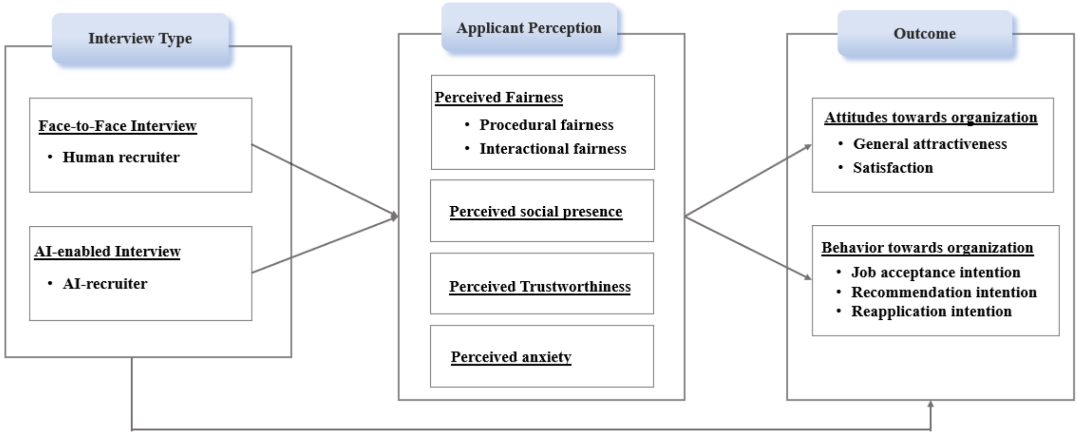

Figure 3.1 The proposed research model.

3.2.3 Applicant Perception

A wide range of perceptions has been studied so far, such as procedural justice (Bauer et al. 2001), anxiety towards AI-enabled interview (Eißer et al. 2020), attitudes towards AI-enabled selection in general (Macan et al. 1994, Chan et al. 1998). The justice perspective originates from (Gilliland 1993), who proposed that applicants' fairness perceptions have a direct impact on subsequent attitudes and behaviors. Specifically, they predicted that applicants who perceive unfair treatment during an interview are predicted to be less inclined to accept a job offer or recommend the employer to others.

According to the growing body of literature, the term applicant perceptions has been defined as the *"attitudes, emotions, or thoughts an individual might have about the R&S process*." (Ryan and Ployhart (2000) p. 566). One of the earliest theoretical models of applicant perceptions aimed to link previous research with organizational justice theory. It elucidates how applicants' perceptions of justice develop and consequently, influence various outcomes in the selection process (Gilliland 1993) and post-hire work-related attitudes and behaviors (Hausknecht, Day et al. 2004, Athota, Budhwar et al. 2020). The fundamental argument of justice theory in the interview process is how applicants perceive interview procedures in terms of the four aspects mentioned above and how these perceptions subsequently impact their future attitudes and behaviors. Ryan and Ployhart (2000) extends the theoretical framework of applicant reactions by introducing additional antecedent and moderating variables. The framework includes the individual's affective and cognitive states during the selection process. Ryan and Ployhart (2000) evidenced these variables are possible determinants of personal and organizational outcomes.

Perceived fairness

In the realm of organizational justice theory, researchers have identified three types of justice, that is, distributive Justice, procedural Justice, and interactional Justice. The first aspect distributive justice, is the outcome of a decision and the perception of the applicant whether this outcome (e.g., pay and workload distribution) is fair (Gilliland 1993). Procedural justice refers to the perceived fairness of the personnel selection procedure. It is focused on fairness in the decision-making process. Interactional Justice, also referred to as interpersonal Justice, is centered on fairness in how individuals are treated. Since distributive justice is more related to the post-hire stage, perceived fairness in this study refers to procedural Justice and interactional Justice.

According to Gilliland (1993) fairness model, perceptions of procedural justice are related to different justice rules. Generally, employment interviews conform to many of the rules, such as enabling two-way communication or the opportunity to perform one's credentials and skills. Cober et al. (2004) revealed the major differences between traditional face-to-face and technology-mediated recruitment, which are communication type, content, functionality of job ads, and design of online recruitment. Meanwhile, Bauer, Truxillo et al. (2004), and Chapman et al. (2003) suggested that face-to-face communication is considered to be fairer than that of technology-mediated communication. Some researchers suggest that the perception of fairness in the selection process depends on the cognitive process (Janssen et al. 2011), and it is also influenced by the ease of information retrieval, communication ways, and applicants' personality and experience.

It is important to understand how the applicants view the selection process (Thielsch et al. 2012) because the perception of fairness is important to applicant perceptions (Macan, Avedon et al. 1994, Bauer, Truxillo et al. 2004). Furthermore, it may be associated with outcome favorability. Previous research has shown that fairness perception could be a predictable variable for job acceptance intentions, organization attractiveness (Hausknecht et al. 2004, Sylva and Mol 2009), job-pursuit intention (LaHuis et al. 2007), and actual job offer acceptance result (Harold et al. 2016).

Perceived trustworthiness

In a comprehensive review of the literature on applicant reactions to the R&S process, trust is an area that has not garnered substantial attention in applicant reactions research, yet it holds the potential to be recognized as a crucial predictor of applicant behavior (Mun and Hwang 2003). Although the literature on applicant reactions has not delved deeply into the subject of trust, the broader academic literature has explored this concept more extensively. For instance, it has been observed that when citizens maintain a general sense of trust in the political process, they are more inclined to participate in various activities, such as voting (Van Ingen and Bekkers 2015). Similarly, in organizational contexts, when employees have trust in their supervisor's fairness, they are more inclined to openly communicate, engage in decision-making processes, and provide feedback (Gao et al. 2011). Karunakaran (2018) and Ticona and Mateescu (2018) have revealed that employees tend to perceive lower levels of trust in decisions when the decision maker is an AI, as opposed to a human.

Considering the novelty of using AI-enabled tools in the recruitment process, it is reasonable to anticipate that some applicants may place trust in the technology, while others may not. However, existing literature on trust indicates that applicants who have confidence in AI-enabled job application systems are more inclined to participate in and have positive behavior intentions (Langer, König et al. 2019, Langer, König et al. 2020, Roulin, Wong et al. 2022).

Perceived social presence

Social presence was first proposed by Short et al. (1976). It aims to explain that in the process of computer-mediated communication and interaction, communicators can have a stronger perception of being with others, and thus obtain a similar sense of face-to-face communication (Short, Williams et al. 1976). The theory lays a theoretical foundation on the interaction with media that can be viewed, explained, and understood. Since then, the theory has been widely used in communication (Short, Williams et al. 1976, Kreijns et al. 2022), online education (Cheikh-Ammar and Barki 2016, Kim et al. 2016), human-computer interaction (Oh et al. 2018, Basch et al. 2020), e-commerce (Cyr et al. 2007, Chen et al. 2023) and other fields.

The social presence of AI-enabled interviews plays a crucial role in reducing the psychological distance between applicants and recruiters, thereby fostering higher levels of experience in the interview process (Basch, Melchers et al. 2020, Hunkenschroer and Luetge 2022). According to Walter et al. (2015), humans perceive a sense of social presence when there is an element of interpersonal warmth and empathy evident during an interaction. Typically, this perception is conveyed through nonverbal communication, as noted by Chapman, Uggerslev et al. (2003). Hence, applicants may experience a reduced sense of social presence in AI-enabled interviews. Even though virtual characters are expected to have a positive impact on social presence (Lee and Nass 2003), individuals in FTF interviews may still convey a greater sense of social presence.

Perceived anxiety

The evaluative and competitive nature inherent in the job application process is prone to evoke feelings of anxiety and apprehension (Rynes et al. 1991). This is especially true for the employment interview, where applicant anxiety can manifest even among the most experienced and adept individuals. Conversely, characteristics exhibited by the interviewer can play a mitigating role in reducing the level of anxiety experienced by the applicant. Following emotional contagion theory (Hatfield et al. 1993), emotions felt by one person (such as the interviewer) can be ‘caught’ by another person (the applicant). In practical terms, this implies that a warm and friendly interviewer is likely to evoke similar feelings in the applicant, thereby reducing anxiety.

Conversely, the characteristics of the interviewer can alleviate the anxiety levels experienced by the applicant. As per the emotional contagion theory (Hatfield, Cacioppo et al. 1993), emotions felt by one person (e.g., the interviewer) can be ‘caught’ by another person (the applicant). In practical terms, this implies that a warm and friendly interviewer is likely to evoke similar feelings in the applicant, thereby reducing anxiety.

In addition, applicant anxiety has the potential to impact perceived organizational attractiveness and subsequent intentions to accept a job. When applicants undergo distress and uneasiness during interviews, they may perceive the organization as less attractive, leading to a diminished likelihood of accepting a job offer (McCarthy and Goffin 2004). Hausknecht, Day et al. (2004) reveal that applicants who respond positively to selection processes are more inclined to view the organization favorably. This positive perception correlates with stronger intentions to accept job offers and a greater likelihood of recommending the employer to others.

3.2.4 Outcome

The variety of outcomes examined in the context of applicant reactions has steadily increased both theoretical frameworks and empirical investigations over time (Nikolaou, Georgiou et al. 2019). This line of research gained significance as it was theorized that applicants’ responses to the selection process could influence a range of outcomes. These outcomes include their willingness to accept employment offers and subsequent post-hire work-related attitudes and behaviors, such as job satisfaction, organizational commitment, well-being, job performance, and turnover (Hausknecht, Day et al. 2004, Athota, Budhwar et al. 2020). Therefore, it can be argued that the outcome can be understood as a response to the applicant’s perception.

Attitudes towards organization

The main outcome studied by researchers is organizational attractiveness. Organizational attractiveness refers to the perceptions related to a company’s or organization’s appeal or image. It is the process through which a prospective employee perceives an organization as the most desirable place to work (Aiman-Smith et al. 2001, Ehrhart and Ziegert 2005, Ahamad 2019). In recent years, organizations have recognized that their appeal to potential employees is crucial for their ability to both attract and retain talent (Collins and Kanar 2013). Organizations have increasingly recognized that their appeal as an employer, as perceived by potential employees, is pivotal to their ability to attract and retain top talent (Collins and Kanar 2013). It is shown that there is a positive relationship between applicant perceptions and organizational attractiveness (Kluger and Rothstein 1993, Rynes and Connerley 1993, Macan, Avedon et al. 1994, Bauer et al. 1998). organizational attractiveness thereby is one of the key elements of the outcome variables.

Behavior towards organization

Scholars have increasingly focused on the behavioral intentions of applicants, yet research in this domain remains limited. The applicants' behavioral intentions refer to offer acceptance intentions (Truxillo et al. 2002), application intentions (Rafaeli 1999), retesting intentions (Madigan 2000), and recommendation and reapplication intentions (Ployhart and Ryan 1998). Moreover, Hunthausen (2000) and (Ryan et al. 2000) studied work performance and applicant withdrawal respectively. Researchers also proved that applicant perceptions have been linked with a variety of behavioral intentions.

Notably, applicant perceptions have been associated conceptually with various post-hire work-related outcomes such as job performance, turnover, and satisfaction (Gilliland 1993). Moreover, Armitage and Conner (2001) pointed out that intentions and behaviors tend to be moderately related. Therefore, applicant perceptions should be associated with actual behaviors (recommendation, reapplication behavior, etc). However, little research exists to date that tests these propositions. Therefore, applicant behavior can be understood as a response to applicant perception, as explained in this study. The concepts of behavioral intention encompass job acceptance intention, pursuit intention, and recommendation intention.

3.3 Methods

3.3.1 Literature Retrieving and Eligibility Criteria

The present meta-analysis was conducted following the guidelines of the Preferred Reporting Items for Systematic Review and Meta-Analyses (PRISMA) statement (Moher et al. 2009, Moher et al. 2015). Several constructs that bear similar connotations but vary in the manipulations were summarized and merged as a single construct. In detail, this meta-analysis framework includes two independent variables, four mediators, and two dependent variables.

Following IS meta-analysis research, relevant articles were retrieved from multiple electronic databases, including Web of Science, ScienceDirect, and Google Scholar.

The literature search was performed independently by the two independent research assistants. The search string was a combination of keywords as follows: ("AI interview" OR "artificial intelligence interview" OR "automated interview" OR "digital interview" OR "AI recruitment" OR "artificial intelligence recruitment") AND ("reaction" OR "respondent" OR "perspective").

The keywords of these elements were searched in the title, abstract, and/or keywords of the databases to obtain the primary studies. Additionally, to identify as much literature as possible, we conducted a supplementary search (i.e., backward searches, manual searches of relevant journals, and forward searching (Jalali and Wohlin 2012)).

Totally, 523 papers were retrieved (see Figure 3.2) and further screened to ensure the paper was eligible for the current meta-analysis when they (1) investigated applicants' reactions to interviews; (2) reported the statistical data such as sample size, and offered the path coefficient, Pearson correlation that can be converted to correlation; (3) were English-language papers published in a high-standard journal. Moreover, studies were excluded if they (1) investigated users' reactions to other AI systems; (2) examined AI systems; (3) included a sample size of less than 30; and (4) were case reports or review articles. A total of 42 relevant studies met the selection criteria and were coded.

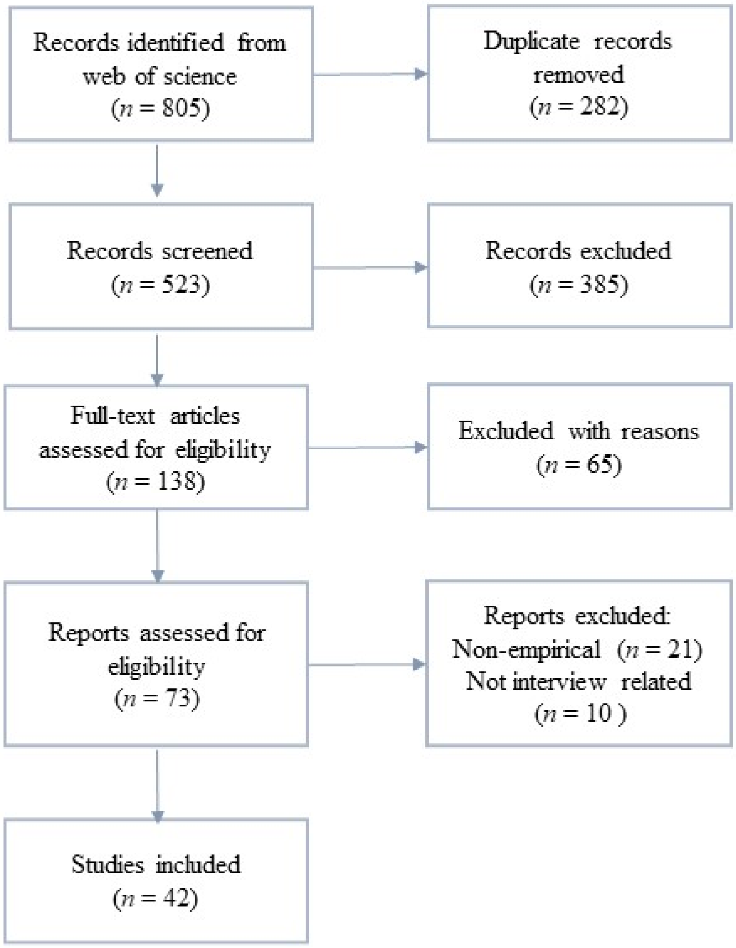

Figure 3.2 The PRISMA flow chart.

3.3.2 Coding

Two PhD candidates took responsibility for the coding process which followed the coding criteria with independent code standards, and this process aligned a 90% coding consistency agreement rate. Sample size, t-test, F-test, path coefficient, and Pearson correlation coefficient were collected and coded reported in previous papers. Given the applicant perception-related features and elements were not consolidated in various literature, we extracted similar elements as consistent variables and averaged estimates of same relationships but recorded estimates separately when variables were independent of each other (Mou and Benyoucef 2021).

3.3.3 Effect Size and Data Analysis

Following the meta-analysis procedure, R Software ($metafor$ package) was adopted to calculate correlations (Assink and Wibbelink, 2016). However, the literature included in this study may have reported with different standards, such as correlations or β coefficients.

Consequently, according to the formula presented by (Peterson and Brown, 2005; Rosenthal and DiMatteo, 2001), all reported statistics were converted into Pearson's correlation coefficient (r). By using random-effect models, the sample-weighted (r was calculated. Furthermore, to assess the heterogeneity, Q values and I^2 values were calculated for each relationship (Borenstein et al., 2009). Subsequently, the relationships of correlations were estimated by weighting each observed correlation which relied on the sample sizes. In case of the measurement error, Hunters and Schmidt's method was used to correct it (Schmidt, 2015; Schmidt and Hunter, 2004).

Publication bias, also known as file-drawer bias, may be present when the likelihood of a study being published on the statistical significance of its findings (Sutton, 2009). In other words, studies with significant results are more likely to attain published opportunities than non-significant results (Lin and Chu, 2018; Thornton and Lee, 2000). It is a significant issue in meta-analysis research. For avoiding publication bias, Failsafe-N (FSN), first described by Rosenthal and DiMatteo (2001), is calculated. The FSN number is the number of missing studies averaging a z-value of zero that should be added to make the combined effect size statistically insignificant. The formula is

$$FSN = \frac{N_{failsafe}}{5k+10},$$

where k is the number of correlations and $N_{failsafe}$ refers to the number of null effect studies that lower a significant effect to a significant level. If the value of FSN exceeds 1, there is no publication bias. In detail, the fail-safe N ratio of this meta-analysis ranks from 77 to 6002, which is higher than 1. Therefore, there is no publication bias in this research.

3.4 Results

This meta-analysis comprised 42 studies, encompassing a combined sample size of 79407 participants and 207 independent correlations. The results of the sample-weighted mean effect sizes were interpreted following the comparing thresholds for correlation that a correlation coefficient of 0.1 is regarded as a weak level; a correlation coefficient ranged from 0.3 to 0.5 represents a moderate level; a correlation coefficient of 0.5 or higher means strong level (Cohen 1992).

Table 3.1 summarizes the effect of independent variables on outcome. It presents the sample-weighted mean correlations of each relationship. For outcome, attitudes towards organization ($r = -0.153$, p <0.01), and behavior intention ($r = -0.209$, p <0.001) with AI-enabled vs Human are at a significant weak-to-medium and a strong level, respectively.

Table 3.2 presents the sample-weighted mean correlations of independent variables on mediators. AI-enabled vs Human shows a significantly strong level of association with perceived justice ($r = -0.275$, p <0.001). The associations of AI-enabled vs Human with perceived social presence ($r = -0.254$, $p < 0.01$), trustworthiness ($r = 0.419$, $p < 0.01$), and anxiety ($r = 0.124$, $p < 0.01$) are all at a significant weak-to-medium level.

Table 3.3 presents the sample-weighted mean correlations of mediators on outcome. It shows that perceived justice ($r = 0.474$, $p < 0.001$), perceived social presence ($r = 0.597$, $p < 0.001$), trustworthiness ($r = 0.218$, p <0.001), and anxiety ($r = -0.433$, $p < 0.001$) yield a strong level of association with attitudes toward organization.

Meanwhile, the associations of perceived social presence ($r = 0.464$, p <0.001) and trustworthiness (r =0.284, p <0.001) with behavior intention are at a significantly strong level. The correlations between perceived justice ($r = 0.327$, $p < 0.05$), anxiety ($r = -0.146$, p <0.01), and behavior intention demonstrate a significant weak-to-medium level with perceived social presence.

Table 3.1 Correlations of independent variable on outcome.

Variable relationship	Relationships identified	Effect Size							
		k	N	r-weighted	Lower bound	Upper bound	Homogeneity (Q)	I2	Fail-safe N
X → Y	Antecedents on outcomes								
	AI vs Human -> Attitudes toward organization	25	6509	-0.153**	-0.254	-0.049	413.057***	94.19	898
	AI vs Human --> Behavior	31	6461	-0.209***	-0.294	-0.122	395.149***	92.408	2651

Table 3.2 Correlations of the independent variables on mediators.

Variable relationship	Relationships identified	Effect Size							
		k	N	r-weighted	Lower bound	Upper bound	Homogeneity (Q)	I2	Fail-safe N
X → M	Antecedents on outcomes								
	AI vs Human --> Justice	31	8577	-0.275***	-0.248	-0.1	363.320***	91.743	1695
	AI vs Human --> Social presence	18	3076	-0.254**	-0.419	-0.073	462.859***	96.327	1132
	AI vs Human -->Trustworthiness	5	1176	0.219**	0.163	0.622	88.338***	95.472	254
	AI vs Human --> Anxiety	14	1709	0.124**	0.043	0.203	36.375***	64.261	77

Table 3.3 Correlations of mediators on outcome.

Variable relationship	Relationships identified	Effect Size					Heterogeneity Test		Test for Publication Bias
		k	N	r-weighted	Lower bound	Upper bound	Homogeneity (Q)	I^2	Fail-safe N
M → Y	Mediators on outcomes								
	Justice --> Attitudes toward organization	19	4980	0.474***	0.374	0.563	320.246***	94.379	6002
	Justice --> Behavior	26	26942	0.327*	0.022	0.429	1183.47***	97.888	2640
	Social presence ---> Attitudes toward organization	8	1775	0.597***	0.538	0.651	23.658***	70.411	1668
	Social presence ---> Behavior	7	1942	0.464***	0.36	0.557	46.755***	87.167	842
	Trustworthiness --> Attitudes toward organization	5	1979	0.218***	0.164	0.271	6.279*	36.294	121
	Trustworthiness --> Behavior	6	2229	0.284***	0.213	0.353	15.469**	67.677	263
	Anxiety --> Attitudes toward organization	4	542	-0.433***	-0.529	-0.325	6.5	53.848	114
	Anxiety --> Behavior	8	11570	-0.146**	-0.245	-0.043	112.043	93.752	298

3.4.1 Key Findings

The field of applicant reactions emerged during the late 1980s and early 1990s in response to various influences, including business, ethical, technological, and scientific factors (McCarthy, Bauer et al. 2017, Kaibel, Koch-Bayram et al. 2019, Nørskov et al. 2020, Griswold et al. 2022, Manroop et al. 2022, Mirowska and Mesnet 2022, Oostrom et al. 2023). Subsequent theoretical and empirical research has expanded our comprehension of the significance of examining the selection process from the applicant's perspective (McCarthy, Bauer et al. 2017, Nikolaou, Georgiou et al. 2019, Hassan et al. 2020). The current study presents an updated theoretical model of applicant reactions and empirically tests different aspects of this model through meta-analysis. The results illustrated that applicants' reactions to AI-enabled interview is different from the reactions to FTF interview. In addition, applicant perceptions are correlated with various organizational outcomes and behavior intentions, many of which hold practical significance for organizations.

Firstly, the results that confirm a link between interview formats and applicant behavioral intentions are consistent with the existing understanding of how different interview methods can impact applicant responses (Straus et al. 2001, Chapman, Uggerslev et al. 2003, Bauer, Truxillo et al. 2004, Folger, Brosi et al. 2021, Oostrom, Holtrop et al. 2023). Specifically, FTF interviews tend to elicit more positive behaviors. FTF interview involves real-time interactions with human interviewers, which can create a more personal and engaging experience for applicants. They can establish a connection with the interviewer and perceive the process as more dynamic and responsive. Moreover, the finding that the application of AI-enabled interviews may decrease organizational attractiveness aligns with some common concerns and challenges associated with the use of AI in the recruitment process. Several factors can contribute to this outcome. AI-enabled interviews can be perceived as impersonal and mechanical, especially when they rely on automated algorithms or chatbots. The lack of immediate human interaction can make applicants feel that the organization does not prioritize personalized communication and engagement. It's important to note that these findings can have implications for organizations and their recruitment strategies. Understanding the impact of interview format on applicant behavioral intentions can help organizations make informed decisions about the design and implementation of their interview processes. It may also influence how organizations use technology, including AI, in the recruitment process, with a focus on creating positive applicant experiences and favorable behavioral outcomes.

Secondly, the findings of this study confirm that applicants' reactions to AI-enabled interview is quite different from the reactions to FTF interview. In terms of perceived fairness, it is noteworthy that an FTF interview is perceived as fairer than an AI-enabled interview. It is inconsistent with the previous research which proposed that employing

AI in interviews is advantageous, as AI interviewers remain impervious to emotional biases stemming from personal, psychological, or physical attributes and other external conditions that human interviewers may be influenced by (Acikgoz et al. 2020). The perception that human-based interview is deemed as fair may be attributed to their characteristic of involving personal interaction with a human interviewer. This feature can lead applicants to believe that they can present themselves more genuinely, allowing for a more comprehensive assessment of their qualifications, personality, and other attributes. While AI-enabled interviews are frequently perceived as less equitable due to their perceived impersonality, which may result in a reduced consideration of the unique qualities and circumstances of applicants. Moreover, they tend to exhibit lower transparency in their decision-making processes. Even more, AI-recruiter may potentially fall into the "uncanny valley" effect. When a robot or character closely resembles a human but has subtle imperfections, it can trigger our brain's ability to detect anomalies. The brains are highly tuned to detect inconsistencies, and these inconsistencies can be unsettling. Similar results are evident in terms of perceived trustworthiness, human-based interview is perceived as the most trustworthy.

In terms of perceived social presence, applicants tend to rate FTF interviews more favorably than AI-enabled interviews. It is consistent with the previous research (Langer, König et al. 2019, Langer, König et al. 2020). FTF interviews typically involve human interviewers on the other end of the interaction. This human presence creates a more natural and familiar sense of social interaction. Applicants can engage in real-time conversations, receive immediate feedback, and establish a personal connection with the interviewer. Moreover, it's entirely understandable that applicants generally rate human-based interviews more favorably in terms of perceived fairness compared to AI-enabled interviews. Human-based interviews involve real-time interactions with human interviewers, creating a more engaging and dynamic conversation. Applicants can establish a personal connection, engage in back-and-forth dialogues, and experience a more empathetic and enjoyable exchange.

Finally, the findings of this study confirm applicant perceptions are significantly correlated with various organizational outcomes and behavior intentions. The study reveals that perceived social presence and perceived fairness significantly influence applicant attitudes toward the organization and their behavioral intentions. It is consistent with the research that demonstrates that a positive interview experience can result in applicants forming a more favorable impression of the organization (Cable and Judge 1997, Amaral et al. 2019, Ho et al. 2021). Moreover, a positive experience, characterized by high social presence and fairness, can increase the likelihood of applicants expressing positive behavioral intentions. They are more likely to accept job offers, speak positively about the organization, and consider future interactions with the company.

3.4.2 Contribution

This study has integrated previous literature and developed a theoretical model that bridges AI-enabled interviews, applicant perceptions, and behavior. The findings fill the knowledge gap in existing studies by enhancing the understanding of applicant perception and behavior intention.

Secondly, this study has confirmed the viability and internal coherence of the mediating mechanism, as determined by SOR framework, through an assessment of applicant perception of fairness, trustworthiness, social presence, and fairness. Subsequently, the relative significance of each mediating factor is ranked that emotional value has the profound effect on individual behaviors.

Finally, this research offers more substantial conclusions in response to certain disputed discoveries. Surprisingly, there is inconsistency with previous literature that AI-enabled interview is considered the least fair. The perception of fairness is a complex and multifaceted issue, and it can depend on numerous variables. Organizations and researchers should continue to study and refine the use of AI in interviews while addressing concerns related to bias, transparency, and user experience to improve the perceived fairness of these tools.

In terms of practical implications, our research is beneficial for organizations and AI recruiter designers. Firstly, Individuals who view the selection tools and processes as fair and directly related to the job tend to develop a more favorable image of the company. They are also more inclined to share positive feedback with others and express a greater willingness to accept a job offer from that organization. Organizations that pay attention to these applicant perceptions can reap a multitude of benefits. On the contrary, organizations that use selection tools and procedures seen unfavorably by applicants may struggle to attract talented candidates and may face a higher risk of litigation or negative public relations.

Moreover, organizations might hesitate to collect applicant reactions due to concerns about attracting unwanted attention or the potential for litigation action regarding their interview process. Nonetheless, these apprehensions can potentially be mitigated if organizations gain a deeper understanding of the aspects of the interview process that could minimize unfavorable reactions. Even research that involves investigating perceptions of current employees on how they perceive current or proposed interview procedures would be helpful to enhance the realism and generalizability of this research. Further investigation is necessary to better pinpoint the specific causes behind adverse applicant reactions. Selection specialists should exercise caution in their choice of these tools when applicant reactions are a significant consideration.

3.4.3 Limitations

Several limitations deserve attention. Firstly, some of the relationships reported are based on small sample sizes. The limited sample sizes prevented separate analyses based on factors such as test type (e.g., cognitive ability tests vs. personality inventories). These factors could potentially influence the nature of the relationship between applicant reactions and organizational outcomes.

Secondly, the stage of the selection process could not be meaningfully assessed for various outcomes, despite both conceptual and empirical evidence suggesting that effects might differ depending on when measurements are taken. To gain a more comprehensive understanding of this subject, further primary studies are needed to shed light on these potential moderating influences. Conducting additional primary research studies will not only help enhance our comprehension of these potential moderators but will also allow researchers to integrate meta-analysis with path analysis, enabling the testing of theoretical models related to applicant reactions.

There is still much left to discover in the field of applicant reactions to AI-enabled interviews. While the data from this meta-analysis serves as a valuable compilation of existing empirical findings, it should not be regarded as the definitive conclusion in this area. Notably, several aspects of this study rely on a limited number of studies, a circumstance that becomes especially pronounced when examining measurements separated in time. Indeed, the existing body of evidence remains limited, making it challenging to draw definitive conclusions regarding the impact of applicant reactions on subsequent behaviors (Ryan and Ployhart 2000, LaHuis, MacLane et al. 2007, McCarthy, Bauer et al. 2017, Nikolaou, Georgiou et al. 2019). Moreover, numerous opportunities remain for future research to expand upon these findings, shedding more light on the nature and significance of these relationships. These directions are outlined next.

Firstly, it is evident that applicants' perceptions are associated with various attitudes and intentions. Only a limited number of studies have followed applicants into their job roles to explore potential spill-over effects on their performance (Gilliland 1994, Hunthausen 2000, Jordan et al. 2019). To ascertain whether there are robust relationships between applicants' perceptions to interview process and subsequent job performance, more research is needed to be conducted.

Future research should also build upon the existing studies that have investigated applicant withdrawal intention (Ryan, Sacco et al. 2000, Truxillo, Bauer et al. 2002, Anderson et al. 2010, Manroop, Malik et al. 2022). Organizations concerned with applicant retention, especially in the context of retaining top applicants (as discussed by Murphy (1986) and Saks and Uggerslev (2010)), should monitor how reactions compete with other factors in explaining self-selection out of the interview stage. There is also a scarcity of studies that have been able to trace the perceptions of applicants who opt out of the whole hiring process. Conducting longitudinal studies of perceptions among applicants who transition into job incumbents would serve to test Gilliland

(1993) argument that initial impressions formed during the selection process might be linked to other attitudes and behaviors once they are on the job, including organizational citizenship behaviors, organizational commitment, and turnover.

Secondly, conducting a more detailed examination of global attitudes towards employment interviews would provide valuable insights into the factors influencing individuals' overall positive or negative perceptions of the hiring process. This line of research, as seen in the works of Arvey, Strickland et al. (1990), and Lounsbury et al. (1989), diverges from the commonly adopted justice-based perspective and merits additional consideration in future investigations. Currently, there is a lack of comprehensive understanding regarding the factors that lead applicants to form enduring positive or negative impressions of interview processes. Delving into basic psychological research on impression formation, as exemplified by studies like Coovert and Reeder (1990), is likely to be instrumental in bolstering the theoretical connections among the multitude of variables typically encompassed in studies on applicant reactions.

Another additional opportunity for future research entails the investigation of the antecedents of applicant reactions. Gilliland and Steiner (2001) have comprehensively documented factors leading to perceptions of unfairness, encompassing elements specific to the testing environment, such as interactions with hiring personnel and distinct attributes of the selection test. Ployhart and Harold (2004) advocate exploring attributions as the underlying mechanism through which applicants form their reactions to the selection process.

Finally, additional research is essential to investigate the potential advantages of interventions designed to improve applicant reactions. Some of these interventions could be directed at ameliorating interpersonal and informational justice, which may include offering explanations for the utilization of selection tools (Ployhart et al. 1999, Walker et al. 2015). Other studies could explore how AI recruiters to effectively convey information about selection procedures impact applicant reactions. Moreover, advancements in technology have enabled rapid feedback delivery and the provision of test information in various formats. These areas call for further research to ascertain how these developments affect applicant perceptions and outcomes.

4 What Drives Job Applicants' Reactions and Behavior Intention

4.1 Introduction

Recruitment is the process of actively looking for and hiring applicants for specific positions or job roles. It involves many steps, from job advertisement to the use of different software to the determination of applicant lists, and finally screening and interviewing applicants according to predetermined criteria. The applicant interview is a vital component of the hiring process. If done effectively, the interview enables the employer to determine if an applicant's skills, experience, and personality meet the job's requirements and the corporate culture. Moreover, it can help contain the organization's long-term turnover costs. Applicants also benefit from an effective interview, as it enables them to determine if their needs and interests would likely be met.

In recent years, there have been significant changes in the format of job interviews. Traditional interviews involve a face-to-face conversation, which can take a behavioral, competency-based, or situational approach. Technology-enhanced interviews have been developed from telephone interviews to videoconference interviews, digital interviews, and now AI-enabled interviews (Brenner, Ortner et al. 2016, Chamorro-Premuzic, Winsborough et al. 2016). AI-enabled interview is a software program that uses virtual characters to conduct job interviews with applicants. It can ask questions, evaluate responses, and even analyze facial expressions and body languages to assess an applicant's suitability for a given position. It is now blossoming all over the world (Brenner, Ortner et al. 2016, Chamorro-Premuzic, Winsborough et al. 2016) and is considered a valuable asset in today's "war for talent" (Leicht-Deobald et al. 2022).

Given the novelty of AI applications in recruiting practice, the subject is still an emerging topic in academic literature (Hunkenschroer and Luetge 2022). Allal-Chérif, Aranega et al. (2021) conducted a review of available technologies to improving the successive stages of the recruitment process. In particular, with the wide application of AI technology, people are increasingly interested in the role of AI technology in the R&S process (Woods, Ahmed et al. 2019). As this early stream of research on organizational actions grew, a new line of research emerged in which both the theoretical frameworks and empirical studies focused, not just on organizations' actions, but on applicants' reactions (Langer, König et al. 2017, Nikolaou, Georgiou et al. 2019, Langer, König et al. 2020). Most of these researches focused on applicant reactions to selection rather than recruiting. This line of research was considered important because applicants' reactions to selection were hypothesized to affect a variety of outcomes, including applicants' performance on selection assessments (e.g., cognitive tests, work samples, interviews), applicants' acceptance of job offers, and various post-hire work attitudes and behaviors (e.g., job satisfaction, organizational commitment, well-being, resilience, job performance, turnover, see (Hausknecht, Day et al. 2004).

Several studies have been studied about the effects of AI-enabled interviews on applicant reactions. Most applicant reaction research is based on Gilliland's (1993) work on applicant reactions to selection systems. Gilliland described several procedural and distributive justice rules. Adhering to the justice rules within selection procedures should positively affect important outcomes such as organizational attractiveness (Chapman et al., 2005). Since the current study investigates the reactions to different kinds of interview procedures, it focuses on the procedural part of Gilliland's model.

Previous research has shown that technology-enhanced interviews can improve efficiency and flexibility. Applicants have a positive perception of selection procedures performed by an AI (Langer, König et al. 2020, van Esch, Black et al. 2021, Figueroa-Armijos, Clark et al. 2022, Horodyski 2023, Meng 2023). Some researchers claimed that potential job applicants are likely to perceive a selection process conducted by an AI as more satisfactory and more just than the same process conducted by a human (Langer, König et al. 2019). Since it minimizes human bias in the hiring process. By relying on algorithms and data-driven assessments, they reduce subjective judgments based on personal biases, ensuring fairer evaluations of applicants.

However, the research has also found negative impacts of AI-enabled interview methods in terms of applicant reactions, fairness perception, and interviewee performance ratings (Blacksmith, Willford, & Behrend, 2016; Chapman, Uggerslev, & Webster, 2003; Sears, Zhang, Wiesner, Hackett, & Yuan, 2013, (Kleinlogel, Schmid Mast et al. 2023, Lavanchy, Reichert et al. 2023), Oostrom, Holtrop et al. (2023)). For instance, videoconference interviews are perceived as less fair and offer less opportunity to perform than face-to-face interviews (Chapman et al., 2003; Sears et al., 2013). Furthermore, AI-enabled interview seems to evoke even less favorable reactions than videoconference interviews (Langer et al., 2019) because of lower social presence. The technological evolution of the interview continues. Currently, the use of highly automated interviews is burgeoning (Langer et al., 2019). Within such interviews, sensors (cameras, microphones) in combination with algorithms and virtual visualization automate the entire interview process (Langer et al., 2019). Scholars have asserted that theoretical research lags behind practical applications (Konradt et al. 2020, Figueroa-Armijos, Clark et al. 2022, Nørskov et al. 2022). In addition, due to technological progress, high-speed internet, and anthropomorphic virtual characters, it is possible to create a conversation quality that can come close to FTF communication. Therefore, it is unclear to what degree these results hold nowadays. Moreover, the empirical findings on the overarching relationship between AI-enabled interviews and applicant reactions remain inconclusive. In summary, despite concerns about the impact on applicants, practical applications of this technology are advancing faster than theoretical research in the field. Thus, in this study, to fill this disagreement gap in the related study and contribute to the design of the AI recruiter, this study investigates applicant reactions to AI-enabled interviews, and how these factors affect applicants' behavior intention. Thus, the research question of this paper is as follows:

(1) *What factors affect applicants' reactions and behavior during the AI-enabled interview?*

(2) *What is the internal relationship between these factors during AI-enabled interviews?*

(3) *Which factors are necessary or sufficient for applicant behavior intention?*

The remainder of this chapter is organized as follows. Section 4.2 and section 4.3 introduce the research model and hypotheses development followed by the research methodology description in Section 4.4. Results are shown in Section 4.5. Section 4.6 discusses the findings, implications, and limitations of this study. The final one is related to the conclusion.

4.2 Theoretical Background

4.2.1 Factors Differentiating FTF and AI-enabled Interview

The different delivery of personnel assessment processes (e.g., face-to-face interviews versus AI-enabled interviews) can affect assessment results and constructs being measured during research, leading to the assumption that interviewee reactions to these interview approaches are likely to differ as well. This study compares face-to-face to AI-enabled interviews, using AI-enabled interview tools that can be used for various contexts. Comparing face-to-face and AI-enabled interview approaches regarding acceptance leads to a variety of features that might differ between those two interview formats.

Two aspects differ between face-to-face and AI-enabled interviews: the decision agent and the object of communication during the interview. Decisions in modern HRM procedures might not necessarily be made by humans (Ötting and Maier 2018). In the case of AI-enabled interviews, the interview tool might independently decide how to react to a given interviewee. Furthermore, the tool evaluates the interview responses and recommends only the top applicants for the next selection stages. In such cases, the AI tool is the decision agent. In face-to-face interviews, however, the decision agent is a human interviewer. In addition to the agent of communication, the interviewer of the AI-enabled interview is a virtual character. In other words, the interviewee communicates with the virtual character instead of the human. This study follows the example of Langer, König et al. (2020) that an AI-enabled interview uses a virtual character interview.

In addition to the differences between AI-enabled interviews and face-to-face interviews that can be deducted from Potosky (2008) model, Potosky (2008) framework provides a theoretical background to generate ideas about potential differences between the interview formats (Langer, König et al. 2019, Langer, König et al. 2020, Langer, König et al. 2020, Langer, Baum et al. 2021, Roulin, Wong et al. 2022). It also provides an idea of how these attributes influence the selection process. Next, we will briefly introduce Potosky's framework that distinguishes between four attributes (i.e., social bandwidth, interactivity, transparency, and privacy concern).

The first aspect is social bandwidth. It is associated with the exchange of information during the communication process (Potosky 2008). It is related to social signals exchange. Media platforms with extensive social reach facilitate the exchange of diverse social signals. During an FTF interview, the social bandwidth needs to be robust. This is because humans engage in the transmission and reception of a wide array of verbal and nonverbal cues in such a scenario. During AI-enabled interview, participants and virtual characters have the capability to exchange social signals. However, it's notable that the social bandwidth in such scenarios is expected to be relatively lower. This is primarily attributed to the current limitations of automated technologies, which are not as adept as humans in recognizing and effectively conveying communicational content.

Interactivity refers to direct communication. According to William's three-dimensional construct, interactivity includes control, exchange of roles, and mutual discourse (Williams et al. 1988). It emphasizes the ability to engage with a communication partner. Media with high interactivity afford direct responses to communication partners. Consequently, AI-enabled interview tends to exhibit lower interactivity compared to FTF interviews. This is attributed to participants interacting with a virtual character, and the adaptation to interviewees is automated (Baur et al. 2013, Gebhard et al. 2014, Gonzalez, Liu et al. 2022, Köchling, Wehner et al. 2022, Kleinlogel, Schmid Mast et al. 2023, Roulin, Pham et al. 2023, Suen and Hung 2023). Even the most AI-enabled interviews currently available do not provide the same level of interactivity, such as the capacity to pose open-ended questions, as observed in FTF interviews (Frauendorfer et al. 2014, Kleinlogel, Schmid Mast et al. 2023, Roulin, Pham et al. 2023).

Transparency refers to whether applicants realize obstacles during the communication process (Potosky 2008). The transparency of a media is considered high when participants are unaware that they are communicating through a medium, and when there are no hindrances during the communication process (Potosky 2008). As an example, transparency would be low in situations where video or audio interferences occur during AI-enabled interviews (Potosky 2008). Nevertheless, in the absence of interferences, individuals are inclined to forget that they are communicating through technology, enhancing the transparency of FTF interviews over AI-enabled ones (Langer, König et al. 2017). Furthermore, communicating with a human recruiter might be much more familiar than interacting with a virtual character tool. This might also reduce transparency in AI-enabled interviews because participants do not understand what is happening during such an interview (Potosky 2008, Roulin, Wong et al. 2022, Kleinlogel, Schmid Mast et al. 2023, Roulin, Pham et al. 2023).

The last variable of Potosky's framework is surveillance (Potosky 2008). It refers to the extent to be perceived as observable by others during the interaction. High surveillance implies that the involved parties are cognizant of the interaction being recorded and subsequently accessed by others (Langer, König et al. 2017). Since many people use technologies, they might be concerned about their performance being videoed and monitored. Regarding AI-enabled interviews, it becomes considerably less apparent whether the interview process is recorded, if individuals are observing the process in real-time, or if the recordings are later reviewed by unauthorized individuals (Langer, König et al. 2017).

Furthermore, even if the objective surveillance in both versions of the interview is equal (e.g., recording of the interview), people might perceive more surveillance in the case of an AI-enabled interview (Barry and Fulmer 2004, Figueroa-Armijos, Clark et al. 2022) because it might be less certain what happens with one's data during such interviews (which, again, is also an issue of low transparency). Thus, perceived surveillance of a highly automated interaction could be more severe (McCole et al. 2010, Hunkenschroer and Kriebitz 2023).

Such specification of the wide range of factors that might affect interview performance provides a richer, fuller, context-inclusive lens for in-depth studies. In the following paragraphs, this paper investigates AI-enabled interviews following this framework, as well as aim to shed light on applicants' potential reactions to the AI-enabled interview concerning.

4.2.2 Social Presence

First proposed by Short, Williams et al. (1976), social presence refers to the "degree of salience of the other person in the interaction and the consequent salience of the interpersonal relationships". Social presence theory aims to explain that during computer-mediated communication and interaction, communicators can have a stronger perception of being with others, and thus gain a sense of similar to in-person communication (Short, Williams et al. 1976). The theory lays the theoretical foundation for interactions with media that can be viewed, explained, and understood. It is believed that the above attributes determine the perception of social presence (Oh, Bailenson et al. 2018, Kreijns, Xu et al. 2022). Since then, the theory has been widely used in communication (Oh, Bailenson et al. 2018, Kreijns, Xu et al. 2022), online education (Cheikh-Ammar and Barki 2016, Kim, Song et al. 2016, Kim et al. 2022), human-computer interaction (Heerink et al. 2008, Frey 2015), e-commerce (Cyr, Hassanein et al. 2007, Chen, Chen et al. 2023), AI-enabled recruitment (Basch, Melchers et al. 2020, Basch et al. 2021), and other fields.

With the continuous evolution of the theory, many scholars have examined social presence from the perspective of social factors rather than just technical factors. Fortin and Dholakia (2005) indicated that interactivity is an important factor influencing social presence. Han et al. (2015) contended that immediacy-related characteristics (e.g., immediate feedback) and intimacy-related characteristics (e.g., privacy and responsiveness) of social networking sites can affect the sense of social presence. Most researchers confirmed that besides the technical factors of media, social factors during interaction such as emoticons, and interactive communication skills also affect the sense of social presence, and their impact is sometimes more significant than technical factors (Walther 1995, Gunawardena and Zittle 1997, IJsselsteijn et al. 1998).

Much of the current literature on social presence pays attention to its impact on different types of behavior intentions of users. In social commerce, perceived interactivity, perceived sociality, and other technical features affect the perception of social presence, thus affecting their participation intention (Zhang et al. 2014). A large number of studies have proven that social presence is a central factor, directly or indirectly affecting other factors of usage to a significant degree, and plays an important underlying role in the overall process of adoption and continuing usage (Shin 2012, Wang and Lee 2020).

4.2.3 Perceived Fairness

During the recruitment process, perceived fairness refers to procedural and distributive justice (Van Vianen et al. 2004). The first aspect is distributive justice, that is the outcome of a decision and the perception of applicant whether this outcome is fair (Gilliland 1993). The concept of procedural justice refers to the fairness of rules and procedures that are used by organizations in making personnel selection decisions (Hausknecht, Day et al. 2004). In this paper, the focused AI-recruiting interview is part of these procedures. Therefore, procedure justice will be particularly discussed in the following. Cober, Brown et al. (2004) and Cober, Brown et al. (2003) revealed the major differences between traditional and AI-enabled recruitment. These differences are evident in forms of communication, the content and functionality of job ads, and the design of online recruitment.

Some researchers suggest that the perception of fairness in the selection process depends on the cognitive process(Janssen, Müller et al. 2011), and it is also influenced by the ease of information retrieval, communication ways, and applicants' personality and experience. Bauer, Truxillo et al. (2004), and Chapman, Uggerslev et al. (2003) suggested that face-to-face communication is considered to be fairer than that AI-enabled communication. Truxillo and Bauer (1999) conducted a field study to reveal the information variables are important in fairness perception. Moreover, the perception of fairness could be explained not only by the way of communication but also by the psychological distance(Anderson and Patterson 2010).

Gilliland (1993) original applicant reactions model, which is based on organizational justice theory, posits that procedural justice or fairness mediates the relationship between characteristics of the selection system and applicant reactions. Research shows that procedural justice perceptions of applicants might change throughout the selection process, as applicants have varying expectations in each stage (Konradt, Oldeweme et al. 2020). Hence, an examination of the fairness perceptions of selection methods with a high degree of digitalization compared to those with a low degree of digitalization in consideration of the respective stage of the application process appears to be meaningful.

In search of possible antecedents of interviewee perception differences, one might refer to Gilliland (1993) fairness model of applicant reactions. According to this model, fairness perceptions of a selection procedure are related to different justice rules. Furthermore, these fairness perceptions can influence important outcomes like perceived organizational attractiveness or applicants' behavioral intentions (Hausknecht, Day et al. 2004) and also their actual job offer acceptance (Harold, Holtz et al. 2016).

The Stimulus-Organism-Response (SOR) model was initially proposed by Woodworth (1929) based on the stimulus-response theory. Later, the model was extended by adding the organism's element (Mehrabian and Russell 1974, Jacoby 2002). Since then, the framework has been used to understand human behaviors (Shah, Yan et al. 2020). Stimulus refers to the environmental factor (Song, Yao et al. 2021). The organism is associated with an individual's affective and cognitive state. It mediates the effect between stimulus and responses (Wu and Li 2018).

In this study, the SOR framework was used to explain the mechanisms by which attributes of AI-enabled interviews affect applicants' behavior intention. Previous studies have shown that attributes proposed by Potosky support applicants' reactions and behavioral intentions, but they also raise negative concerns (Fox and Vendemia 2016, Sun et al. 2021). In this study, we use attributes of AI-enabled interviews as a stimulus. When people perceive the positive or negative effects of attributes, they may trigger various psychological reactions (Langer, König et al. 2020) . Based on the conceptual framework of social presence proposed by Sun, Fang et al. (2021) and the literature on applicants' reactions to AI-enabled interviews (Langer, König et al. 2017, Langer, König et al. 2018, van Esch, Black et al. 2021), we focus specifically on two aspects of applicants' affective and cognitive state related to the attributes of AI-recruiter: social presence and perceived fairness. In this study, social presence and perceived fairness are defined as organisms. The negative affective and cognitive state may lead to adverse behavior intentions for applicants (Langer, König et al. 2017, Langer, König et al. 2018, Langer, König et al. 2020, van Esch, Black et al. 2021). Behavior intention is, thus, included as an outcome element in this study.

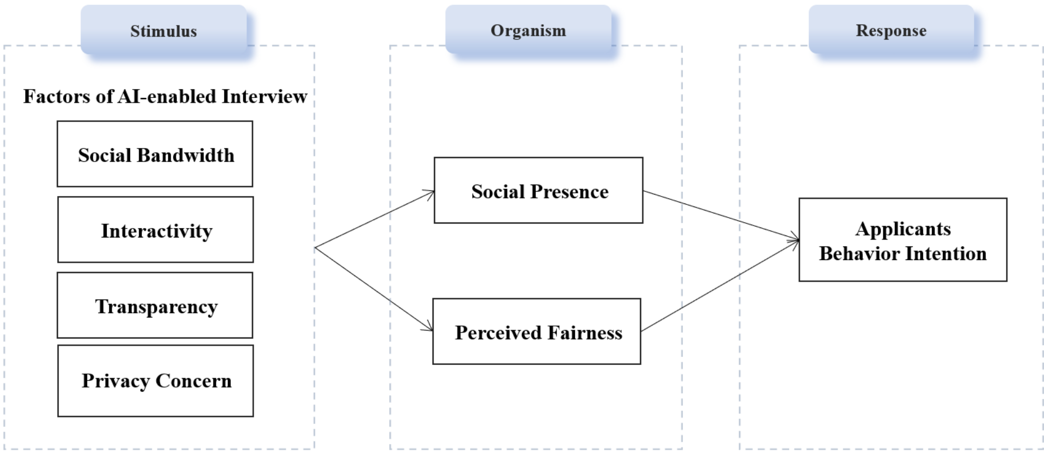

Figure 4.1 The framework of this study.

Further, because intentions and behaviors tend to be related (Armitage and Conner 2001), applicant perceptions should be related to actual behaviors such as job offer acceptance intention, recommending the organization to others, reapplying intention, etc. Job offer acceptance refers to the extent to which job applicants intend to accept job opportunities presented by a particular organization. Rejection from job applicants can significantly frustrate hiring and personnel managers within firms, given the substantial energy, time, and opportunity costs invested in the recruitment process to identify suitable applicants for specific job positions. Consequently, if prospective job applicants ultimately decline job offers, it could result in a considerable waste of organizational resources and time. (Hausknecht, Day et al. 2004, McLarty and Whitman 2016). Therefore, in this study, applicants' behavior intention refers to job offer acceptance intention.

This study focuses on understanding the applicant's behavior intention during the AI-enabled interview and testing the inter-relationship. Figure 4.1 illustrates the framework, more discussions are given in the following sections.

4.3 Hypothesis Development

Social bandwidth is related to one aspect that is also covered by media richness theory (Daft and Lengel 1986), referring to the extent to which a medium allows one to send and receive verbal and nonverbal information (Potosky 2008). Compared with face-to-face interviews, social bandwidth is lower in AI-enabled interviews since media programs hardly show the complete picture of the other person, which can lead to limitations in information delivery (Toldi 2011). While cutting-edge technology portrays an AI-enabled interview where interviewees also send and receive communication information, even the most advanced technology still lacks the same opportunity as interpersonal communications. Therefore, social bandwidth should be relatively lower because AI technologies are still not as good as humankind at discerning and delivering communicational content. In particular, the more communication paths (verbal, non-verbal, para-verbal) a sender uses to deliver information, the better the information is comprehensible by the receiver. Accordingly, with higher social bandwidth, individuals have more cognitive resources available for social interactions. This means applicants can engage more deeply in communicating with virtual characters. This enhanced cognitive engagement contributes to a more vibrant and intellectually stimulating social presence.

In general, interviews meet many of the justice rules that are mentioned in (Gilliland 1993) model, like allowing two-way communication or the opportunity for interviewees to show their qualifications, experiences, and skills. However, given that communication changes through the use of AI, this also means that social bandwidth is linked to perceived fairness (Roulin, Wong et al. 2022). Higher social bandwidth allows individuals to access a more comprehensive set of information (Langer, König et al. 2018). This access enables individuals to participate more actively in social interactions. When people are well-involved, they are more likely to perceive decisions and interactions as fair (Langer, König et al. 2019, Roulin, Wong et al. 2022).

Given that applicants communicate with virtual characters in AI-enabled interviews, the more the virtual character resembles a real person, the higher the exchange of social signals and perceived fairness would be. Thus, we hypothesize:

H1a: *Increased levels of social bandwidth will have a positive impact on social presence.*

H1b: *Increased levels of social bandwidth will have a positive impact on perceived fairness.*

Interactivity refers to the extent to which it is possible to interact during a conversation. Face-to-face interviews allow for direct responses between communication partners. In AI-enabled interviews, lag times may cause a limitation of interactivity (Wegge 2006). AI-enabled interviews provide lower interactivity than FTF interviews because interviewees interact with a virtual interviewer and the adaption to interviewees is also automatized (Gebhard et al. 2018). Even the most intelligent AI tools available today can provide the same level of interactivity as a real person (Köchling, Wehner et al. 2022, Kleinlogel, Schmid Mast et al. 2023, Roulin, Pham et al. 2023). According to William's three-dimensional construct, interactivity includes control, exchange of roles, and mutual discourse (Williams, Rice et al. 1988). It is obvious that interactivity has emerged as an essential factor in interaction with new technology (Fortin and Dholakia 2005) and different media have different levels of interactivity. High interactive media makes it easy to directly respond to applicants. In turn, the applicant would forget they are interacting with a virtual character and increase their social presence (Langer, König et al. 2020, Langer, König et al. 2020, Langer, Baum et al. 2021).

Interactivity allows the AI system to adapt in real time based on applicants' responses. This adaptability ensures that the interview remains relevant and fair for each applicant. This equal opportunity for engagement contributes to a perception of fairness, as all applicants can showcase their abilities and experiences (Roulin, Wong et al. 2022). Moreover, higher interactivity contributes to an improved overall applicant experience. Applicants who feel engaged, heard, and understood during the interview process are more likely to perceive the experience as fair. Positive applicants' experiences can lead to a favorable perception of the fairness of the AI-enabled interview process. Thus, we hypothesize:

H2a: *Increased levels of interactivity will have a positive impact on social presence.*

H2b*: Increased levels of interactivity will have a positive impact on perceived fairness.*

Transparency refers to whether applicants realize obstacles during the communication process (Potosky 2008). Given that face-to-face interviews represent a normal conversational situation, no limitations are expected in terms of transparency, whereas the microphone, camera, and even the image on the screen may reduce the transparency of AI-enabled interviews (Horn and Behrend 2017). AI-enabled interviews would further reduce transparency, as interviewees may lack an understanding of highly automated tools that make it hard for participants to express themselves spontaneously. That is, if participants feel no obstacles, the transparency is high. For instance, transparency would be lower for highly automated interviews (Langer, König et al. 2017). It may be because it is hard for applicants to understand what is happening and what will happen during the interview process (Potosky 2008). This lack of understanding may cause difficulties for applicants in naturally expressing themselves and turn decrease their social presence (Langer, König et al. 2017). Accordingly, if applicants forget they are communicating with technologies, transparency would be high and the perceived social presence and perceived fairness would be accordingly high.

Thus, we hypothesize:

H3a: *Increased levels of transparency will have a positive impact on social presence.*

H3b: *Increased levels of transparency will have a positive impact on perceived fairness.*

Surveillance refers to the fear that a technology-mediated conversation is recorded or monitored, and later accessed by a third party, which can build into greater concerns from applicants on privacy issues (Smith et al. 2011). During AI-enabled interviews, given that the information is transmitted over the Internet, one can never completely avoid conversations being unknowingly recorded, which can lead to a fear of surveillance. In other words, it is less certain whether anyone else is watching the interview process and the whole process is later viewed by an unauthorized individual (Langer, König et al. 2017). Moreover, it might be less clear what happens to a person's data during such interviews (Barry and Fulmer 2004). Hence, it is believed that surveillance of AI-mediated interactions may be more severe (McCole, Ramsey et al. 2010), leading to lower social presence.

Privacy concerns can erode trust in how personal data is handled during AI-enabled interviews (Langer, König et al. 2019, Cardon et al. 2023). If applicants are apprehensive about the security and confidentiality of their information, it creates a sense of mistrust. This lack of trust undermines the perceived fairness of the interview process, as individuals may question whether their data is being treated with integrity (Langer, Baum et al. 2021). Moreover, privacy concerns may lead to a perception of unequal access to information (Cardon, Ma et al. 2023). If applicants are unclear about how their data is being utilized in the decision-making process, it can create a sense of asymmetry (Stahl and Wright 2018, Figueroa-Armijos, Clark et al. 2022). The lack of transparency contributes to the perception that some applicants may have an advantage over others, impacting the fairness of the interview process. Thus, the higher the degree of automated interviews, the more severe the perception of privacy concerns and the low perception of social presence (Barry and Fulmer 2004, McCole, Ramsey et al. 2010). Therefore, we hypothesize:

H4a: *Increased levels of Privacy Concern will have a negative impact on social presence.*

H4b: *Increased levels of Privacy Concern will have a negative impact on perceived fairness.*

The level of social presence can significantly influence one's behavioral intentions. In the online learning environment, the degree of social presence significantly affects students' intentions (Gunawardena 1995). Students who perceive higher levels of social presence tend to express a stronger intention to actively participate in online discussions and collaborate with their peers (Guo et al. 2023). Individuals who experience a higher degree of social presence while shopping online are more likely to have the behavioral intention to make purchases (Biocca 1997, Ye et al. 2020, Chao et al. 2022). Furthermore, social presence in e-commerce live interactions affects consumers' willingness to buy products or services (Wang et al. 2021). Social presence significantly influences individuals' intentions toward social commerce, with the mediation of customers' experiences (Hassan et al. 2018, Liu et al. 2019, Hossain et al. 2023). Lu et al. (2016) discovered that the level of social presence significantly influenced individuals' behavioral intentions in a virtual context. Those who felt a stronger sense of social presence were more inclined to engage in social interactions and activities. Social presence also plays a vital role in online hotel booking intentions (Amin et al. 2021). In the context of mobile social network games, social presence perceived by players has a positive impact on sustainable use intention through a series of mediator variables (Wang and Lee 2020). Social presence also plays a pivotal role in users' intentions to use a chatbot service or a telepresence system (Heerink et al. 2008, Lee et al. 2013, Dinh and Park 2023, He et al. 2023). When the virtual environment provides cues that the system is attentive and responsive to their responses, applicants perceive that their input is valued. This sense of being heard positively influences their behavior and intention to actively participate in the interview process. Positive perceptions of technology influence behavior intention, as applicants are more likely to approach the AI-enabled interview with trust and a willingness to accept.

H5: *Increased levels of social presence will have a positive impact on job offer acceptance intention.*

It is important to understand how the applicant views the selection process (Thielsch, Träumer, & Pytlik, 2012). Because perception of fairness is also important to applicant reactions (Bauer et al., 2004; Macan, Avedon, Paese, & Smith, 1994). Furthermore, it may be associated with outcome favorability. Previous research has shown that fairness perception could be a predictable variable for job acceptance intentions and organization attractiveness (Bauer, Maertz Jr, Dolen, & Campion, 1998; Sylva & Mol, 2009), job-pursuit intention (LaHuis, MacLane, & Schlessman, 2007). Moreover, the recruitment procedure conveys the value of the organization (Dineen & Noe, 2009). It is also consistent with Truxillo and Bauer (1999). They revealed that procedural fairness perception may interact with individual outcomes, that is, acceptance intentions (Gilliland, 1994; Macan et al., 1994). Job offer acceptance refers to the extent to which job applicants intend to accept job opportunities presented by a particular organization. Consequently, if prospective job applicants ultimately decline job offers, it could result in a considerable waste of organizational resources and time (Hausknecht, Day et al. 2004, McLarty and Whitman 2016). These findings are consistent with organizational justice theory. Thus, we hypothesis

H6: *Perceived fairness has a positively influence on applicants' job offer acceptance intention for AI-enabled interviews.*

Figure 4.2 shows the research model to understand the role of attributes of AI-enabled interviews, and the effect on job offer acceptance intention through the mediating effect of social presence and perceived fairness.

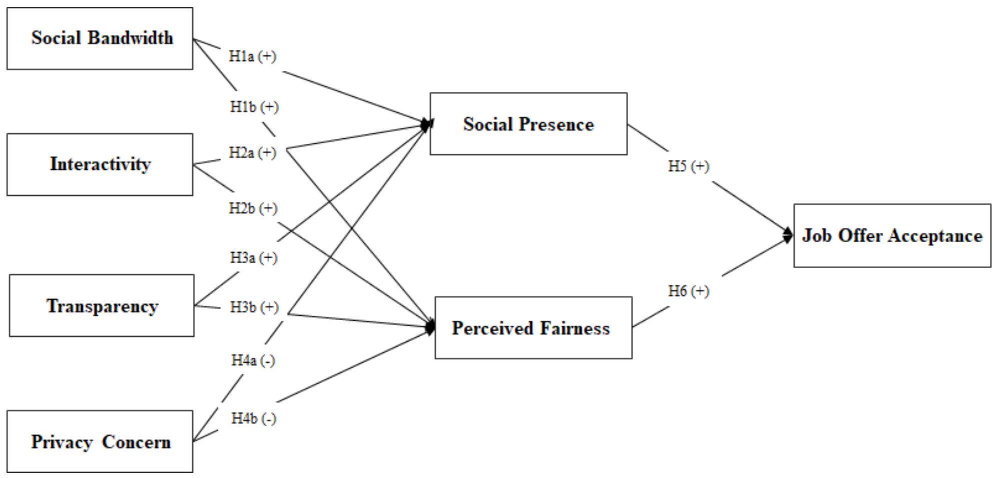

Figure 4.2 Research model.

4.4 Methodology

4.4.1 Data Collection

A pretest was performed to ensure the quality of the questionnaire and translated items were consistent with the original English version. Four HR professionals and four PhD students were involved. The respondents completed the questionnaire and further provided comments. Moreover, minor changes were made.

The primary way to collect data in this study is online questionnaire sampling. To avoid duplication, one respondent accepted one IP address. A short video displaying the AI-enabled interview and online questionnaire was posted to the respondents. Overall, 304 responses were received. After a preliminary data collection, 12 responses are eliminated since replicate IP and incomplete information. Finally, 292 valid responses remained for further analysis. 65% of respondents were male. The mean age was 22 years (SD = 4.47). At the time of the study, 83% of respondents had a bachelor's degree. Half of them (49%) had interaction experience with AI and 14% of respondents had experienced being interviewed by AI. The details are presented in Table 4.1.

Table 4.1 Result of our data collection.

Measures	Items	Frequency	Percentage
Gender	Male	168	58%
	Female	124	42%
Age	<20	29	10%
	20-30	219	75%
	30-40	41	14%
	>40	3	1%
Education	<Bachelor	35	12%
	Bachelor	238	82%

	Master	13	4%
	>Master	6	2%
Income	<4000 yuan	198	68%
	4000-8000 yuan	32	11%
	8000-12000 yuan	14	5%
	12000-20000 yuan	18	6%
	>20000 yuan	30	10%
Interview experience by AI	Yes	50	17%
	No	242	83%
Interaction experience with AI	Yes	144	49%
	No	148	51%

4.4.2 Measurement

For scale development, a pool of items was identified from the extant literature. Table 4.2 presents the 24 items and the reference sources. Participants responded to the items on a scale from 1 (strongly disagree) to 5 (strongly agree). ***Social Bandwidth*** was measured with three items from Chen et al. (2022). ***Interactivity*** was measured with six items. Two were taken from Bauer, Truxillo et al. (2001). Two were taken from Langer, König et al. (2017), and two were self-developed. ***Transparency*** was measured with two items taken from Langer, König et al. (2020). ***Privacy concern*** was measured with three items. One was taken from Malhotra et al. (2004). One was adapted from Langer, König et al. (2018) and one was taken from Smither et al. (1993). ***Social presence*** was measured with five items from Gefen et al. (2003). ***Perceived fairness*** was measured with three items. Two were taken from Bauer, Truxillo et al. (2001) and one was taken from Warszta (2012). ***Job offer acceptance*** was measured with three items from Wehnar et al. (2016).

Table 4.2 Construct and measurement.

Construct	Item	Source
Social Bandwidth (SB)	I think that the AI recruiter would have human-like characteristics.	Chen, Gong et al. (2022)
	I think that the avatar or the voice of the AI recruiter would be like a human	
	I think that the speaking style of AI recruiter would be like human beings.	
	I feel an AI recruiter would facilitate enough	Bauer, Truxillo

Interactivity (IT)	communication during the interview.	et al. (2001), Warszta (2012)
	I would have felt comfortable asking questions about the interview if I had any	
	I am sure that I was in control of the interview	Langer, König et al. (2017)
	Through my performance, I could influence the result of the interview.	
	I feel that using AI recruiter during the interview process would be effective and efficiency.	Self-developed
	Overall, I feel AI-enabled interviews would be highly interactive.	
Transparency (TP)	I feel that using an AI-enabled recruitment process is transparent.	(Langer, König et al. 2020)
	I feel it is obvious what the AI-enabled recruitment process is measuring.	
Privacy Concern (PC)	In such an interview, it is important to me to keep my privacy intact.	Malhotra, Kim et al. (2004)
	Such interviews threaten applicants' privacy.	Langer, König et al. (2018)
	During this interview, I provided private data that will be stored safely.	Smither, Reilly et al. (1993)
Social Presence (SP)	I think that using an AI recruiter during the interview process will provide me with a sense of human contact.	Gefen, Karahanna et al. (2003)
	I think that using an AI recruiter during the interview process will provide me with a sense of sociability.	
	I think that using AI recruiter during the interview process will provide me with a sense of human warmth.	
Perceived fairness (PF)	I think that using an AI recruiter during the interview process was a neutral way to select people.	Bauer, Truxillo et al. (2001)
	I think that using an AI recruiter during the interview process was an unbiased way to select people.	

	All things considered, I feel the interview process was fair.	Warszta (2012)
Job Offer Acceptance (JOA)	I would accept the job if it was offered to me.	McLarty and Whitman (2016)
	This is the job I want	
	Based on my experience with this interview process, it would be great if I could work for the company	

4.4.3 Data Analysis

In the first phase, PLS-SEM was used to test H1–H6. PLS-SEM is appropriate when testing relationships between predictors and an outcome, dealing with non-normally distributed data, and needing greater statistical power (Hair et al. 2011, Sarstedt et al. 2021).

In the second phase, the fsQCA was used to understand how different configurations of the antecedents (i.e., social bandwidth, interactivity, transparency, etc.) lead to different behavioral intentions. The fsQCA is a mixed-methods analytic tool that combines the logic of a non-linear, case-based approach with the tools of statistical testing (Mikalef and Krogstie 2020, Pappas and Woodside 2021). More detailed illustrations of the fsQCA can be found in Pappas and Woodside (2021) study. As per (Pappas and Woodside 2021), the following measures were employed when conducting the fsQCA.

Data calibration. Because all scale measurements use a Likert five-point method. Consistent with the calibration method of Campbell et al. (2016), when the scaled score is 4, it is fully affiliated, when the score is 0, it is completely unaffiliated, and 2 is the intersection point.

Truth table generation. It is included the identification of all possible configurations and case sorting by a minimum frequency of two and a consistency threshold of .75 (Ragin 2009).

Interpretation of results. This paper uses the intermediate solution that is superior to both complex and parsimonious solution (Ragin 2009). The software fsQCA4.1 was used to run the analysis.

4.5 Results

4.5.1 Measurement Model

In this study, structural equation modelling (SEM) was employed to test model. Firstly, to assure the reliability and validity of scales, confirmatory factor analysis (CFA) is conducted. The results of Cronbach's α and factor analysis are presented in Table 4.3. As can be seen, the value of Cronbach's α is greater than the recommended value of

0.8 (Hair 2009), strongly supporting the reliability of constructs. As for the convergent validity, the outer loadings of all constructs are higher than the 0.70 cut-off level (Flynn et al. 2010). Moreover, Composite reliability (CR) and the average variance extracted (AVE) are also calculated. The values of CR are greater than 0.70. Concerning AVE, all values exceed 0.50 (Koufteros 1999). The convergent validity is also acceptable. Discriminant validity was assessed through the Fornell-Larcker criterion (Fornell and Larcker 1981). The results show all square roots of the AVE of each construct are larger than its correlations with all other latent constructs (Hair 2009), which provides strong evidence for discriminant validity, see Table 4.4. Based on these results, all the items were proved to perform well and robust.

Table 4.3 Results for internal reliability and convergent validity.

Construct	Variable	Cronbach's a	Factor loading	CR	AVE
Social Bandwidth (SB)	AP1	0.92	0.81	0.95	0.86
	AP2		0.84		
	AP3		0.72		
Interactivity (IT)	IA1	0.95	0.78	0.96	0.80
	IA2		0.77		
	IA3		0.82		
	IA4		0.79		
	IA5		0.76		
	IA6		0.66		
Transparency (TP)	TP1	0.93	0.86	0.96	0.93
	TP2		0.81		
Privacy Concern (PC)	PC1	0.87	0.83	0.92	0.79
	PC2		0.89		
	PC3		0.86		
Social Presence (SP)	SP1	0.92	0.66	0.95	0.86
	SP2		0.72		
	SP3		0.67		

Perceived Fairness (PF)	PF1	0.89	0.76	0.93	0.82
	PF2		0.73		
	PF3		0.81		
Job Offer Acceptance (JOA)	BI1	0.91	0.76	0.94	0.85
	BI2		0.69		
	BI3		0.72		

Table 4.4 Discriminant validity.

	SB	IT	PF	PC	SP	TP	JOA
SB	0.926						
IA	0.748	0.890					
PE	0.655	0.706	0.905				
PC	0.191	0.095	0.201	0.888			
SP	0.73	0.815	0.84	0.108	0.927		
TP	0.083	0.184	0.154	0.723	0.15	0.963	
JOA	0.821	0.799	0.768	0.171	0.748	0.156	0.920

4.5.2 Structural Model

Based on acceptable reliability and validity of the construct, we further shift focus on the overall fit of the structural model, see Figure 4.3. The result is acceptable since all values have reached the recommended level. Thus, we can further analyze the path coefficient and implications for proposed causal links. Table 4.5 shows the result of hypothesized relationships. Except for the relationship between TP and SP, PC and SP, the rest estimated coefficients are positive and significantly less than 0.05. It indicates that the relationship between these constructs is statistically significance.

Table 4.5 Hypothesis and model path coefficients.

Path	Estimate	P	Result
SB --- >SP	0.25	0.00	H1a: supported
IT --- >SP	0.65	0.00	H2a: supported

TP --- >SP	0.02	0.31	H3a: rejected
PC--- >SP	-0.05	0.13	H4a: rejected
SB --- >PF	0.23	0.00	H1b: supported
IT --- >PF	0.42	0.00	H2b: supported
TP --- >PF	0.11	0.02	H3b: supported
PC--- >PF	-0.13	0.02	H4b: supported
SP --- >JOA	0.29	0.00	H5: supported
PF--- > JOA	0.38	0.00	H6: supported

Based on path coefficients, it is obvious that social bandwidth has a positive effect on social presence with statistical significance (β = 0.25, p = 0.00), and H1a is accepted. Interactivity affects social presence positively (β = 0.65, p = 0.00), supporting H2a. While the effect of transparency (β = 0.02, p = 0.31) and privacy concern (β = -0.05, p = 0.13) are not significant, H3a and H4a are rejected.

Meanwhile, among perceived fairness, social bandwidth (β = 0.23, p = 0.00) and interactivity (β = 0.42, p = 0.00) both show significance, supporting H1b and H2b. The effect of transparency (β = 0.11, p = 0.02) and privacy concern (β = -0.13, p = 0.02) are significant, H2b and H4b are supported. In addition, social presence has significant and positive effects on behavioral intention (β = 0.29, p = 0.00). Moreover, perceived fairness triggers applicants' behavioral intention (β = 0.38, p = 0.02). These elements are consistent with hypotheses H5 and H6.

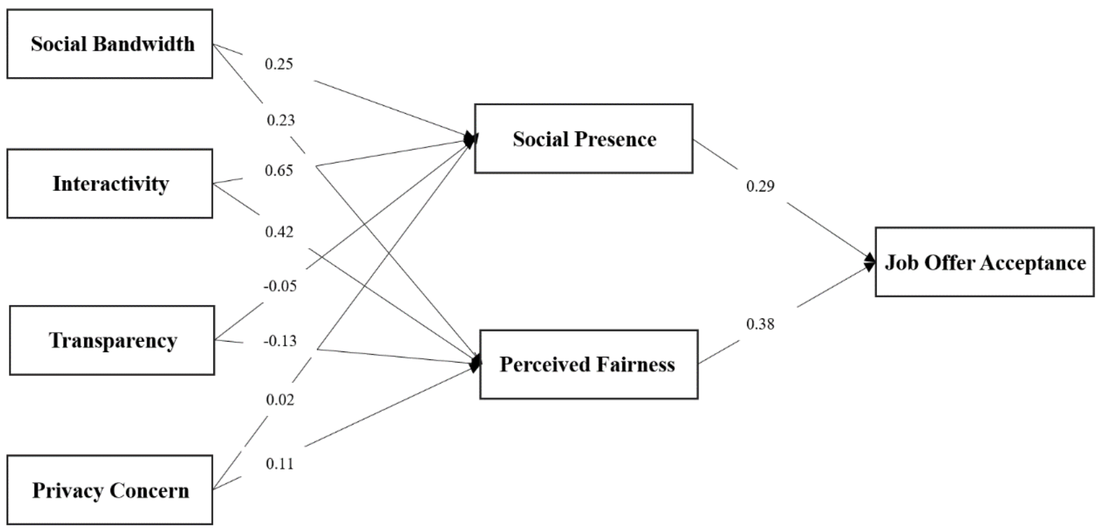

Figure 4.3 The Structural model with estimations of parameters.

4.5.3 The fsQCA Results

The use of the fsQCA can offer several benefits, compared to traditional methods of analysis. To capture combinations of conditions that are sufficient for an outcome to occur, the fsQCA uses both qualitative and quantitative assessments and computes the degree to which a case belongs to a set (Ragin 2000, Rihoux and Ragin 2008), thus creating a bridge between qualitative and quantitative methods. The fsQCA uses calibrated measures, as data are transformed into the [0, 1] range. Calibration is common in natural sciences but not so much in social sciences. It can be used to satisfy qualitative researchers in interpreting relevant and irrelevant variation as well as quantitative researchers in precisely placing cases relative to one another (Ragin, 2008b; Vis, 2012).

Coverage is an important indicator for measuring empirical relevance in QCA research, reflecting the empirical relevance or importance of the configuration (Ragin 2009), similar to R^2 in regression (Fiss 2011).

Next, to improve the presentation of the findings, we transform the solutions from the fsQCA output into a table that is easier to read. Table 4.6 presents the result. Typically, the presence of a condition is indicated with a black circle (●), the absence/negation with a crossed-out circle (⊗), and the "do not care" condition with a blank space (Fiss 2011). Moreover, the large circle (conditions that exist in both parsimonious solutions and intermediate solutions) refers to the core condition and the small circle (conditions that exist only in intermediate solutions) refers to the peripheral condition.

The fsQCA generated four configurations for applicant job offer acceptance intention as shown in Table 4.6. The four configurations can be regarded as sufficient condition combinations of applicants' behavior intention. The findings are readable as follows. Solution 1 (transparency×privacy concern×SOCIAL PRESENCE×perceived fairness) reflects social presence is a core condition. While the absence of transparency, privacy concerns, and perceived fairness play a supporting role. The consistency of solution 1 is 0.53 and the unique coverage is 0.02.

Solution 2 (INTERACTIVITY×transparency×privacy concern×SOCIAL PRESENCE) reflect social presence and interactivity are core condition. The absence of transparency and privacy concerns are peripheral conditions. The consistency of solution 2 is 0.82 and the unique coverage is 0.08.

Solution 3 (SOCIAL BANDWIDTH×interactivity×transparency×privacy concern× social presence) reflects social bandwidth plays a key role. The absence of transparency, privacy concerns, and social presence are peripheral conditions. The consistency of solution 3 is 0.821 and the unique coverage is 0.08.

Solution 4 (SOCIAL BANDWIDTH×INTERACTIVITY×transparency×privacy concern×social presence) reflects social presence and interactivity are core conditions. Interactivity and the absence of transparency and privacy concerns are peripheral conditions. The consistency of solution 4 is 0.94 and the unique coverage is 0.004.

Table 4.6 The fsQCA generated four configurations for applicant behavioral intention.

Casual condition	Solution			
	1	2	3	4
Social Bandwidth			●	●
Interactivity		•	⊗	•
Transparency	⊗	⊗	⊗	⊗
Privacy Concern	⊗	⊗	⊗	⊗
Social Presence	●	●	⊗	⊗
Perceived Fairness	⊗			
Raw coverage	0.5258	0.5192	0.6407	0.5103
Unique coverage	0.0235	0.0788	0.0753	0.0040
Consistency	0.7826	0.8225	0.8075	0.9386
Solution coverage	0.7505			
Solution consistency	0.8215			

4.6 Discussion

4.6.1 Key Findings

This study tested the relationship between attributes of AI-enabled interviews and applicants' job offer acceptance intention based on the conceptual framework proposed by (Potosky 2008). It is suggested that the attributes of AI-enabled interviews affect applicants' perceptions of social presence and fairness, which can further have impactions on their behavior intention.

First, the findings of this study confirm that social bandwidth is significantly and positively associated with social presence and perceived fairness, as suggested by H1a and H1b. The validity of H1 means that the hypothesis on social bandwidth triggers positive behavior intention, by positively influencing social presence and fairness. This empirical study confirms the conceptual framework of the digital interview study proposed by Langer, König et al. (2017). The more the virtual character resembles a real person, the higher the exchange of social signals and perceived social presence and fairness would be. In addition, the findings reveal that high interactivity improves the perception of social presence, supported by H2a. In other words, highly interactive media makes it easy to directly respond to applicants. It is consistent with the conclusion investigated by Langer, König et al. (2020).

Additionally, for complex interview scenarios, the effect of attributes of virtual characters is different from other scenarios. Therefore, it is feasible for the study to link attributes of AI-recruiter to fairness, which compensates for the antecedents of users' negative fairness in AI-enabled interview (Pickard and Roster 2020).

Second, the findings confirm that privacy concerns negatively influence perceived fairness, as postulated in H4b. The support for H4b means that personal psychology burdens (e.g., privacy concerns) affect applicants' perceptions. Applicants may feel uncertain about the use of their data during AI-enabled interviews, which can lead to concerns about privacy (Langer, König et al. 2020) . Specifically, it is less certain whether anyone else is watching the video live or if the video recording is later viewed by an unauthorized individual (Langer, König et al. 2017). Moreover, it might be less clear what happens to a person's data during such interviews (Barry and Fulmer 2004). Applicants who are highly concerned about privacy will spend more time or invest more effort protecting their privacy, and these efforts may cause less fairness. This finding might be worrisome for organizations because previous research has also shown that increased privacy concerns lead to negative behavior intention (e.g., test-taking motivation or recommending the organizations to friends (Bauer et al. 2006)).

Notably, the effect of transparency on social presence is insignificant. Transparency refers to the degree of obstacles during communication and the degree to which conversation partners are aware of technological mediation (Potosky 2008). This was an unexpected result. A possible explanation for this result is that with the advancement of AI, the scope of AI applications is gradually expanding, and people are progressively adapting to collaborating and interacting with AI in various scenarios (e.g., autonomous driving (Di and Shi 2021), virtual assistants (Lugano 2017)). Through these collaborations and interactions, individuals have experienced convenience, efficiency, and personalized services (Roy et al. 2023). Over time, people will likely find that there are fewer barriers to interacting with AI. Moreover, the predominance of a relatively young population in this study sample is an indirect indication that the younger population tends to show a greater level of acceptance and comfort with AI.

Thirdly, the findings of this study confirm that social presence and perceived fairness positively influence the applicant's behavior intention. This is consistent with the findings of existing research (Cramer et al. 2016, Langer, König et al. 2020). The statement implies that if applicants feel a sense of social presence during the AI-enabled interview (perhaps through a more interactive and human-like interaction) and if they perceive the interview as fairness, they are more likely to have a positive intention for actual behaviors or inclination to continue with the interview or the application process. This study echoes the call for more empirical testing of applicant perceptions and actual behaviors (Armitage and Conner 2001).

Finally, by introducing the fsQCA method, this chapter not only enriches the understanding of factors influencing applicants' behavioral intentions but also demonstrates the effectiveness of the fsQCA in analyzing complex decision processes. As a quantitative tool, the fsQCA helps to analyze systemic changes more accurately in complex environments, particularly in analyzing the complexity of applicant reactions and behavior. It was discovered that social bandwidth, social presence, and interactivity are key attributes influencing applicants' reactions. These findings are significant for understanding the mechanisms behind the formation of applicants' behavioral intentions and provide new perspectives for future research in human resource management and organizational behavior.

4.6.2 Contribution

This study has several theoretical implications. This study significantly contributes to the AI-enabled interview literature by employing quantitative methods to examine strategies and what factors influence applicants' perceptions and behavioral intentions. While the AI recruiter has captured substantial interest in the industry, it remains in its nascent stage, and many questions persist regarding ready-to-use this technology for applicants. This study serves as a foundational stepping stone to address these fundamental inquiries. Moreover, this study enriches the literature on AI-enabled interviews from the perspective of job applicants by introducing the social presence theory. By highlighting the intrinsic relationship between AI recruiters' attributes and applicants' behavior intention, this study extends our understanding of how AI-enabled recruiters impact job applicants. This perspective is particularly valuable as it sheds light on the psychological and emotional factors that influence applicants' reactions to AI-enabled recruiters. Secondly, this paper proposes that the effect of attributes of AI-recruiter on social presence is different. Only social bandwidth and interactivity show a significant effect, and the effect of transparency and privacy concern are not significant.

This study also sheds light on some practical implications. The study sheds light on the use of AI-enabled interview providers and provides direction for designing and implementing AI-enabled recruiting strategies. By examining the benefits and challenges of using AI in recruitment, the study offers several implications for organizations. While AI-enabled offers an exciting and flexible means of forming an initial impression of an applicant, organizations need to recognize that they differ significantly from standard interviews. They present unique considerations and challenges that demand careful consideration. Organizations should maintain oversight to ascertain whether AI-enabled interview leads to unexpected behavior such as self-selecting out of the interview process or rejecting the offer. This may occur for various reasons, including applicants' expectations of more interpersonal care from the organization, negative experiences during the interview, and the submission of the interview due to concerns about the handling and storage of their private data by the selected organization. When an organization observes a decline in applicant engagement due to the use of AI-enabled interviews, it may be prudent to consider reverting to traditional interviews or exploring strategies for enhancing applicant experiences in AI-enabled interviews. One idea to address this concern is to provide applicants with information about digital interviews, including what to expect and how to prepare. This could improve applicant reactions and social presence, potentially leading to increased organization attraction, as proposed by McCarthy, Bauer et al. (2017). In addition, improving the perceived fairness is also a key element. Given these findings, organizations need to consider both the benefits and potential drawbacks of using AI-enabled interviews in their hiring processes. While the use of AI can increase efficiency and accuracy, it is important to also address concerns about privacy and ensure that applicants feel comfortable with the use of their data. This can be done through transparency and clear communication about data usage and security measures.

4.6.3 Limitations

There are several limitations for this study while contributing valuable insights into how attributes of AI recruiters affect applicants' behavior has several limitations. Firstly, this research employed a cross-sectional survey methodology, which, although efficient, may be subject to reply bias and self-selection bias. Although this method is still efficient for researchers with limited human and material resources (Yang et al. 2022), it can be better to collect longitudinal data. This approach would enable researchers to trace the evolution of applicants' attitudes and intentions towards the AI-enabled interview over time, providing a more nuanced understanding of how these evolve.

Secondly, it is essential to recognize that this study focused on respondents in China, yet the AI-enabled interview has earned global attention. This raises questions about the generalizability of our findings to other cultural contexts. To address this limitation, future research should consider employing cross-cultural data samples to determine whether the effects of the attributes in this study differ across diverse cultures. This approach will facilitate a more comprehensive understanding of the universality or cultural nuances in applicants' behavior.

Thirdly, personal characteristics, such as gender, personality traits, and belief, may serve as moderators in the relationship among attributes, perceptions, and behavior intention (Chen 2007, Sharma et al. 2012, Hwang and Griffiths 2017, Yang et al. 2020). Jin (2011) proposed belief in a just world moderated the relationship between recruiter type (AI vs. human) and applicants' behaviors. It was observed that individuals perceiving the world as less fair tend to have greater confidence in AI-recruiter providing fair evaluations, leading to increased trust in AI assessments. Furthermore, this group expresses lower satisfaction with human recruiters, along with perceptions of unjust and unworthy behavior. Future research should delve deeper into these individual differences, investigating the impact of variables such as personality traits and background on behavior intentions. This approach will shed light on the diverse motivations and barriers faced by the application of AI-enabled interviews. These identified limitations and proposed research directions pave the way for more comprehensive and globally applicable insights into the understanding of the applicants' behavior intention to AI-enabled interview.

5 Understanding Applicants' Perceptions of AI-enabled Interviews Through the Lens of Regulatory Focus

5.1 Introduction

With the advancements in technology, artificial intelligence (AI) has permeated various industries and workplaces. AI-enabled technologies, including creditworthiness prediction, criminal justice systems, and pricing of goods, have disrupted traditional personnel R&S practices, gaining popularity at an exponential rate (Yarger et al. 2020). Organizations find AI-driven selection tools appealing due to their ability to offer higher speed and efficiency gains compared to traditional screening and assessment methods (van den Broek et al. 2019). In today's competitive job market, these tools are considered valuable assets in the ongoing "war for talent" (Leicht-Deobald, Busch et al. 2022).

Hunkenschroer and Luetge (2022) define AI recruiting as employing AI techniques to aid organizations in the process of recruiting and selecting job applicants. As AI-enabled interview continues to shape the recruitment landscape, it becomes crucial to understand how applicants perceive and react to this emerging personnel selection technology. The perception of AI-enabled interviews by job applicants is a multifaceted phenomenon that can be influenced by various factors. One theoretical framework that offers valuable insights into understanding individuals' perceptions and behaviors is the regulatory focus theory (Higgins 1997).

Regulatory focus theory (RFT) is a psychological framework that examines how individuals adopt different cognitive orientations when pursuing their goals and making decisions (Higgins 1997, Higgins 2012). It holds significant importance in both the realms of psychology and management. This theory posits two primary regulatory focuses: promotion focus and prevention focus. A promotion focus is characterized by a desire to achieve positive outcomes, emphasizing gains, aspirations, and opportunities. In contrast, prevention focuses centers on avoiding negative outcomes, highlighting the prevention of losses, security, and responsibilities. People can exhibit a dominant focus or shift between these orientations depending on the context and their dispositions. Understanding regulatory focus is essential in various domains, including marketing, management, and psychology, as it helps explain how individuals approach tasks, make choices, and respond to challenges, ultimately impacting their motivation, decision-making, and behavior (Brockner and Higgins 2001, Gorman et al. 2012, Lanaj et al. 2012, Fruhen et al. 2015, Bozer and Delegach 2019).

In this context, this study aims to explore how applicants' regulatory focus orientation and regulatory fit influence their perceptions of AI-enabled interviews. The RFT offers a valuable lens through which to study applicants' reactions to AI-enabled interviews for several compelling reasons. First and foremost, job applicants often have multifaceted goals, such as achieving a positive outcome (promotion focus) by securing a desirable job or avoiding a negative outcome (prevention focus) such as rejection or unfavorable evaluation. Understanding which regulatory focus predominates can shed light on how applicants interpret and respond to AI-enabled interviews. Moreover, the RFT highlights that the unique construal of pleasure/pain goals influences strategic orientation during goal pursuit, shaping perceptions of AI interviews (promotion/prevention focus), and impacting attitudes, motivation, and interview reactions. Additionally, by examining how applicants' regulatory focus influences their responses to AI-enabled interviews, researchers and practitioners can gain insights into improving the interview experience, enhancing applicant motivation, and optimizing selection processes, all of which have implications for recruitment and HR management.

The RFT offers a comprehensive framework to investigate the nuanced interplay between applicants' goal orientations and their reactions to AI-enabled interviews. This paper aims to explore and examine applicants' perceptions of AI-enabled interviews from a regulatory focus perspective. Through a comprehensive literature review and empirical research, we seek to shed light on the factors that influence applicants' perceptions, the role of regulatory focus in shaping these perceptions, and the implications for organizations utilizing AI in their interview processes. Ultimately, this research contributes to a deeper understanding of the human side of AI-enabled interviews and provides practical insights for organizations to optimize their recruitment strategies and enhance applicant experiences.

5.2 Theoretical Background

5.2.1 Regulatory Focus Theory

Proposed by Higgins (1997), the Regulatory Focus Theory (RFT) is a psychological theory that has gained significant attention in recent years. RFT posits that individuals may engage in self-regulation with a *promotion focus* or a *prevention focus*. Individuals who are promotion-focused and prevention-focused differ in three key aspects. Firstly, they differ in their motivation orientation. Secondly, they differ in their achievement goals and standards. Thirdly, they differ in the types of outcomes that are important to them. Promotion-focused individuals prioritize hopes, accomplishments, and gains, and are motivated to pursue positive outcomes and personal growth to realize their "ideal self". In contrast, prevention-focused individuals prioritize safety, responsibility, and avoiding potential losses or negative outcomes, and seek security and safety by adhering to guidelines and rules to realize their "ought self". Research has shown that promotion-focused individuals tend to be more creative, risk-taking, and optimistic, whereas prevention-focused individuals are typically more cautious, detail-oriented, and vigilant (Kark and Van Dijk 2007). Individuals' regulatory focus can be shaped by both their self-regulation history and experience, which can become a chronic personality trait, as well as the current situation or task, which can influence their temporary motivation orientation (Molden et al. 2008).

These motivational orientations have important implications for human behavior and the decision-making process. Individuals with different regulatory focuses have significant differences in thinking, cognition, and information processing (Tumasjan and Braun 2012). Studies have shown that individuals with a prevention focus tend to adopt systematic information processing methods, analyze, and process information meticulously, and emphasize the accuracy of information processing. Individuals with a promotion focus tend to adopt heuristic information processing methods, simply processing information, with emphasis on the speed of information processing (Förster et al. 2003, Kark and Van Dijk 2007). Compared with other motivation theories, RFT pays more attention to the differences behind different motivations, and incentive strategies caused by these two regulatory focuses. For instance, in the pursuit of career success, some individuals prioritize seizing opportunities for career advancement, while others prioritize job performance and avoiding mistakes. These differences in regulatory focus can lead to divergent paths toward career success, with promotion-focused individuals more likely to take risks and prevention-focused individuals more likely to be cautious. Therefore, RFT can be applied to elucidate how people perceive and make decisions when pursuing their goals. Specifically, it explores the connection between an individual's motivation and the approach they take in striving towards their goal.

From a personality psychology standpoint, individuals with strong promotion goals tend to adopt a strategic approach of actively seeking situations that align with their aspirations. While those with strong prevention goals tend to adopt a strategy focused on avoiding situations that might lead to deviations from their duties (Higgins 1997, Scholer and Higgins 2012). Furthermore, individuals with a predominant promotion regulatory focus tend to favor eagerness-related strategies in their pursuit of goals. These strategies involve creating action plans designed to ensure successful outcomes and facilitate the achievement of their aspirations, which align with their strong concern for accomplishment. Conversely, individuals with a prevention regulatory focus tend to gravitate toward vigilance-related strategies when pursuing their goals. These strategies entail the development of action plans aimed at preventing potential risk and avoiding situations that could impede them from fulfilling their obligations, in alignment with their strong concern for responsibility (Higgins and Spiegel 2004). In this context, regulatory focus can be comprehended as a relatively stable motivational orientation or personality trait. The current study examined the attributes of AI-enabled interviews, chronic regulatory focus as an activated state on applicants' fairness, and feelings of social presence.

This paper introduces regulatory focus theory in the scenarios of AI-enabled interviews. And discuss the impact of differences in applicants' cognitive motivation on their behavior. In the process of AI interview and communication, it is essentially the process of information processing and adoption by applicants. In terms of information acceptance, individuals with a promotion focus are more divergent, have a tolerant attitude towards external things, and are more likely to accept external information. Individuals with a prevention focus are more conservative in their thinking, have a cautious attitude towards external things, and are not easy to accept new information. Therefore, individuals with different regulatory focus types may have differences in the way of information processing and perception during the interview process (TANG and SONG 2020). That is to say, the cognitive traits of applicants themselves potentially affect their feelings during the AI-enabled interview, such as perceived social presence and perceived fairness Therefore, this study will further investigate how promotion and prevention relate to applicants' behavior.

5.2.2 Regulatory Fit and Its Mechanism

Regulatory fit refers to the congruence between an individual's motivational orientation and the characteristics of the environment or task they are engaging in (Higgins 2000). When individuals' motivational orientation aligns with the characteristics of the task or environment, they experience a sense of regulatory fit, which enhances their motivation and performance. For example, promotion-focused individuals would experience regulatory fit when engaging in tasks that offer opportunities for advancement, growth, and achievement, while prevention-focused individuals would experience regulatory fit when engaging in tasks that require careful attention to detail and risk management.

Specifically, regulatory fit theory emphasizes the importance of the relationship between an individual's goals for a specific activity and the way they approach that activity (Higgins, 2000). During the process of pursuing goals, individuals with different regulatory orientations have their preferred strategies. Promotion-oriented individuals tend to use an eagerness-related strategy, whereas prevention-oriented individuals tend to employ a vigilance-related strategy. When individuals with different regulatory orientations use their preferred behavioral strategies, they achieve regulatory fit (Higgins 2000). Therefore, there is a match between promotion orientation and eagerness-related strategy and a match between prevention orientation and vigilance-related strategy.

The sensation of being "right" or "wrong" can be influenced by the perception of how well an individual's regulatory focus aligns with their goal-pursuit strategies (Aaker and Lee 2006, Lee and Higgins 2009). Regulatory fit engenders a sense of "feeling right" about an individual's actions, thereby motivating individuals to become more deeply engaged in their activities (Aaker and Lee 2006). Specifically, people enjoy performing actions that help them meet their goals (Carver and Scheier 1999, Freitas and Higgins 2002). Furthermore, individuals tend to experience increased satisfaction when their goal-pursuit strategies lead them toward the accomplishment of significant long-term objectives (Sheldon and Elliot 1999). Regulatory fit occurs when an individual's goal-pursuit strategy aligns with and sustains their regulatory focus.

Prior research has supported the notion of regulatory fit and its impact on motivation and performance. Research has shown that regulatory fit can enhance creativity (Friedman and Förster 2001), reduce cognitive effort (Shah and Higgins 2001), and increase persistence in goal pursuit (Shah et al. 2002). Moreover, regulatory fit has been applied in various domains to explore human behavior. For instance, regulatory fit has been used to develop persuasive messages to encourage healthy behavior, such as exercise and healthy eating (Laran and Janiszewski 2009). In consumer behavior, the regulatory fit has been found to influence product choice, brand preference, and purchase intention (Lee and Aaker 2004). In organizational behavior, regulatory fit has been shown to enhance job satisfaction, motivation, and performance (Brockner et al. 2004).

Given that RFT and regulatory fit have provided a promising framework for understanding individual distinctions in motivation and decision-making, we believe that this theory can help to understand applicants' perception of AI-enabled Interviews and we argue that applicants can also be categorized into those who are promotion-focused and those who are prevention-focused.

5.3 Hypothesis Development

5.3.1 The Effects of Regulatory Focus

Individuals with a promotion-focused regulatory orientation tend to exhibit creativity, and extraversion, and engage in extra-role behaviors at work (Baas et al. 2008). They also display a learning orientation, indicating a desire to acquire new knowledge and skills (Gorman, Meriac et al. 2012). A similar process should apply when companies deploy new personnel recruiting and selection technology, the AI-enabled interview. Promotion-focused applicants are more willing to take challenges and improve themselves based on their ideals, for example, the identity they wish to actualize and the job position they wish to obtain (Neubert et al. 2008). Meanwhile, individuals with a promotion focus are more likely to be drawn toward hedonic benefits as hedonic value provides pleasurable experiences leading to the fulfillment of promotion goals (Chernev 2004, Chitturi et al. 2007). In other words, promotion-focused individuals enjoy hedonic experiences more.

At least one paper relates to the relationship between fairness perceptions and regulatory focus theory. Liberman et al. (2005) sought to investigate whether loss aversion (as predicted by prospect theory (Kahneman and Tversky 1979)) applied to framed gains (i.e., gains and non-gains). They argue that prior research focused only on framed losses (i.e., non-loss and losses). Unable to fully explain fairness and affect findings using loss aversion, they proposed that regulatory focus theory (Higgins 1997) might help to explain individuals' different strategic approaches to gain frame (a promotion focus) and loss frame (a prevention focus) conditions.

The present study extends this regulatory focus related research, by looking specifically at the impact of regulatory focus on fairness perceptions. Further, to date, research defining regulatory focus as either a personality characteristic (trait) or a situational variable (state) largely overlooks alternative process variables. We focus on one such process variable shown in the fairness. Hence individuals with promotion focus in their AI-enabled interview are more likely to indulge in experiencing perceived fairness. This leads us to the following hypotheses:

H1a: During the AI-enabled interview, individuals with a promotion focus (VS prevention focus) have higher perceived fairness.

A growing body of research has examined the various types of social presence in diverse interactive media environments. These include social presence in a text-to-speech interface (Lee and Nass 2005) social presence in human-robot interaction(Lee et al. 2006), and perceived social presence in virtual experiences (Jin 2010). Presence refers to a psychological state in which the virtual self is experienced as the actual self in either sensory or no sensory ways (Lee 2004). Furthermore, this study delved into the impact of regulatory fit on applicants' perception of presence, as a robust sense of presence plays a pivotal role during the AI-enabled interview process (Sylaiou et al. 2008). Feelings of social presence are influenced by endogenous variables in new interactive media environments (e.g., interface evaluations, and parasocial interactions with virtual characters). During AI-enabled interviews, applicants use computers as a medium of interaction, and hence presence plays a critical role in the social interaction of the users. As discussed above, considering that employee focus on promotion versus prevention influences how employees perceive and react to interactive media environments (Brockner and Higgins 2001), we argue that perceived social presence is associated with their regulatory focus. Because promotion-focused individuals are open to new experiences (Vaughn et al. 2008), they are more willing to embrace change and new technology rather than stability (Liberman et al. 1999). As for AI-enabled interviews, we expect that promotion-focused applicants with lower resistance to accepting the new selection process would enhance their perceptions of social presence. Therefore, it can be hypothesized that:

H1b: During the AI-enabled interview, individuals with a promotion focus (VS prevention focus) have a higher perceived social presence.

5.3.2 The Effects of Regulatory Fit

The different promotion quests and prevention concerns give rise to different strategic preferences in goal pursuit: eagerness versus vigilance, respectively. Individuals who have a promotion focus tend to favor eagerness-related strategies for pursuing their goals, such as creating action plans to ensure everything goes smoothly and facilitate the realization of their ambitions. This approach aligns with their focus on achievement. In contrast, individuals who have a prevention focus tend to prefer vigilance-related strategies for pursuing their goals, such as creating action plans to prevent things from going wrong and fulfilling their obligations. This approach corresponds to their focus on responsibility (Higgins et al. 2003).

Relevant to our research question, regulatory fit effects have been used in communication, e.g., to form attitudes towards products (Lee and Aaker 2004) or to influence behaviors (Latimer et al. 2008). Strategic framing of message arguments in a way that fits the recipient's regulatory focus has been shown to relate to greater persuasiveness. Research on regulatory fit suggests that it influences attitudes through three mechanisms: processing fluency (ease of processing and comprehensibility), a strengthened engagement (greater involvement and attention), and the *feeling right* experience. The latter one is not a pleasant hedonic experience, but rather relates to a sense of "rightness" or "correctness" (Higgins 2011).

As discussed previously, applicants are keenly attuned to the matters of justice during the interview process, and especially when they are informed of an unfavorable outcome, they are interested to learn *how* it came about. This question relates to process fairness. There is evidence that "feeling right" from regulatory fit transfers to fairness or moral perceptions: "If it feels right, it is right" (Camacho et al. 2003). For instance, regulatory fit increases the perceived morality of another person's deeds and the righteousness of a public policy (Camacho, Higgins et al. 2003). Roczniewska et al. (2018) demonstrated that a regulatory fit between an employee and an organizational climate produces perceptions that the company's prevailing procedures are fair. These transfers are possible because people confuse the sources of their experiences and use available information for judgments (Van den Bos et al. 1997) in line with the feelings-as-information heuristic (Schwarz 2002). In line with the previous literature (Brockner 2011), we propose that applicant reactions to organizational change are a function of process fairness. Thus, perceived fairness will be higher when applicants feel right. We hypothesis:

H2a: Individuals in regulatory fit condition (promotion strategy for individuals with promotion focus; prevention strategy for individuals with prevention focus) have higher perceived fairness.

Beyond replicating previous findings about the effects of regulatory fit on fairness, the present study examined the role of regulatory fit in inducing applicants' perceptions of social presence during AI-enabled interviews. Moreover, the current work investigated how regulatory fit affects applicants' perception of presence, as a strong sense of presence is central to the virtual recruitment experience (Sylaiou, Karoulis et al. 2008). Presence refers to a psychological state in which the virtual self is experienced as the actual self in either sensory or no sensory ways (Lee 2004). During AI-enabled interviews, applicants use computers as a medium of interaction, and hence presence plays a critical role in the social interaction of the users. The sense of regulatory fit between regulatory focus and goal-seeking strategies can make applicants feel right, well-fitted, and immersed. These feelings can consequently cause applicants to feel that the avatar were their real self via the mechanism called "perceptual illusion of nonmeditation"(Lombard and Ditton 1997). Jin (2011) found that regulatory fit within 3D virtual reality (VR) increases users' feelings of presence. Therefore, the current study argued that the regulatory fit that media applicants experience increases their feelings of presence during AI-enabled interviews. Thus, we hypothesize:

H2c: Individuals in regulatory fit condition (promotion strategy for individuals with promotion focus; prevention strategy for individuals with prevention focus) have a higher perceived presence.

5.4 Methodology

5.4.1 Participants and Design

This experiment recruited 136 participants, all of whom were recent college graduates in a job-seeking status. All participants had prior experience with job interviews, and everyone volunteered to take part in the experiment.

The experimental task of this study is to assume that the subject is in the place, and the experimental participants evaluate the perceived social presence and perceived fairness without considering other irrelevant factors. The experiment employed a two (regulatory focus state: promotion versus prevention) × two (regulatory strategy:

eagerness means versus vigilance means) between-subjects design.

The study generally replicated the experimental procedure from a few previous regulatory focus experiments (Freitas and Higgins 2002, Keller 2006, Hong and Lee 2008) in the novel context of AI-enabled interviews. Following Shah et al. (1998), the eagerness-related strategy group emphasizes pursuing gains with a promotion focus, while the vigilance-related strategy group emphasizes avoiding losses with a prevention focus. In other words, the eagerness-related strategy refers to the strategy of achieving goals through the pursuit of objectives, while the vigilance-related strategy involves strategies to ensure success by preventing errors or mishaps (Higgins 2000). The video watched by participants consists of the introduction of AI-enabled interviews and the strategy of the assessment. Specifically, AI recruiters evaluate interviewees' performance in four aspects: language expression ability, judgment ability, organizational ability, and innovation ability, assigning scores accordingly. The content watched by the eagerness-related group is when the AI recruiter assesses the interviewer, it uses a basic score of 60 points. During the interview process, the AI recruiter discovers the applicant's strengths and merits from the four aspects mentioned above and then adds points for applicants. Thus, the applicant's total score is finally obtained. Whereas the content watched by the vigilance-related group is when the AI-recruiter assesses the interviewer, it uses a basic score of 100 points. During the interview process, the AI recruiter discovers the applicant's strengths and defects and then subtracts points from 100 points. Thus, the applicant's total score is finally obtained. After the subjects watching the video, they were asked to accurately retell the AI-recruiter's evaluation method to ensure the effectiveness of the strategy.

5.4.2 Experimental Procedural

Data collection began by inviting students to a lab equipped with computers on which video was preinstalled and running. Before the experiment starts, the subjects need to read the experimental instructions carefully to ensure that they clearly understand the experimental content and procedures. Afterward, the subjects sat in front of the computer and formally entered the experiment.

The formal experiment is divided into two phases. The first phase is to obtain the subject's regulatory focus. The subjects firstly watch the video, which is the introduction of AI-enabled interviews. They can watch repeatedly without a time limit to fully understand and feel the scenario of an AI-enabled interview. Then, the subjects experienced the AI-enabled interview.

They filled out the questionnaires about regulatory focus. After all the subjects finish the questionnaire, the system will calculate the scores of the subjects in the two subscales of the promotion and prevention focus and calculate the average value. And then subtract the promotion focus score from the prevention focus score. The difference is arranged in order of magnitude, and finally, the median A dichotomous method was used to obtain the subject's orientation type (Higgins et al. 2001). The study involved 68 participants with a promotion-oriented focus and another 68 participants with a prevention-oriented focus.

The second phase of the experiment is to trigger the regulatory strategy. Each subject will be randomly assigned the eagerness-related strategy AI-enabled interview and vigilance-related strategy interview. The AI recruiter will ask 6 questions during the interview process. Subjects answer the questions one by one and click on the next question. After all questions have been answered, subjects will be shown how to score. Figure 5.1 shows the interface of AI-enabled interviews. After the subjects finished interviewing, they were asked to fill out the questionnaires about perceived social presence, perceived fairness, and basic information during the experiment.

Figure 5.1 The interface of AI-enabled interview.

5.4.3 Measures

The type of regulatory focus was determined using the method of Higgins (1997). This study employed a Regulatory Focus Questionnaire (RFQ). The RFQ measures accommodation orientation through an individual's subjective history of success in promotion/prevention focus. The questionnaire contains 10 items, of which the prevention orientation contains 5 items, involving the prevention of negative outcomes, such as "How often did you obey rules and regulations that were established by your parents?", "Not being careful enough has gotten me into trouble at times."; Facilitating Orientation also includes 5 questions, such as "How often have you accomplished things that got you “psyched” to work even harder? Finally, we calculate the scores of the subjects in the two subscales of the promotion and prevention focus, calculate the average value, and then subtract the promotion focus score from the prevention focus score. The difference is arranged in order of magnitude, and finally, the median A dichotomous method was used to obtain the subject’s regulatory focus.

For scale development, a pool of items was identified from the extant literature. Table 5.1 presents the 6 items and the reference sources. Participants responded to the items on a scale from 1 (strongly disagree) to 5 (strongly agree). ***Social presence*** was measured with five items from Gefen, Karahanna et al. (2003). ***Perceived fairness*** was measured with three items from Bauer, Truxillo et al. (2001).

Table 5.1 Construct and measurement.

Construct	Item	Source
Social Presence (SP)	I think that using an AI recruiter during the interview process will provide me with a sense of human contact.	Gefen, Karahanna et al. (2003)
	I think that using an AI recruiter during the interview process will provide me with a sense of sociability.	
	I think that using an AI recruiter during the interview process will provide me with a sense of human warmth.	
Perceived fairness (PF)	I think that using an AI recruiter during the interview process was a neutral way to select people.	Bauer, Truxillo et al. (2001)
	I think that using an AI recruiter during the interview process was an unbiased way to select people.	
	All things considered, I feel the interview process was fair.	

5.5 Results

5.5.1 Sample Characteristics

Table 5.2 Demographic statistics of respondents.

Measures	Items	Frequency	Percentage
Gender	Male	72	53%
	Female	64	47%
Age	<20	3	2%

	20-30	132	97%
	>30	1	1%
Education	<Bachelor	4	3%
	Bachelor	128	94%
	Master	2	2%
	>Master	2	1%
Income	<4000 yuan	5	4%
	4000-8000 yuan	120	88%
	8000-12000 yuan	5	4%
	12000-20000 yuan	3	2%
	>20000 yuan	3	2%
Interview experience by AI	Yes	7	5%
	No	129	95%
Interaction experience with AI	Yes	64	47%
	No	72	52%

A total of 136 usable responses were collected, of which 72 were from males and 64 were from females. Most of the respondents were aged between 20 and 30 and had a bachelor's degree. Half of them (49%) had interaction experience with AI and 14% of respondents had experienced being interviewed by AI. The details are presented in Table 5.2.

5.5.2 Results

Table 5.3 Summary of independent samples test.

		t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference
PF	Equal variances assumed	5.330	134	.000	.85	.16
	Equal variances not assumed	5.330	133.910	.000	.85	.16
SP	Equal variances assumed	5.356	134	.000	.77	.14
	Equal variances not assumed	5.356	127.117	.000	.77	.14

Independent samples t-test was conducted to demonstrate the differences between the promotion focus group and the prevention focus group on the perception of fairness and perceived social presence. Table 5.3 presents the results of hypothesis testing. The result of perceived fairness for the promotion-oriented group is $t(134)$=5.33, p = 0.00. This shows that the perceived fairness of the promotion-oriented group is significantly higher than that of the prevention-oriented group, supporting H1a. The prevention-oriented group reported the result of perceived social presence is $t(134) = 5.36$, $p = 0.00$. Thus, H1b is supported, that is individuals with a promotion focus (VS prevention focus) have a higher perceived social presence.

To examine the impact of regulatory fit on perceived fairness and the perception of social presence, the eagerness strategy for individuals with a promotion focus and vigilance strategy for individuals with a prevention focus are merged into a regulatory fit group. Accordingly, the eagerness strategy for individuals with a prevention focus and vigilance strategy for individuals with a promotion focus are integrated into the regulatory misfit group. The results demonstrated a significant two-way interaction effect on perceived fairness and perceived social presence, as plotted in Figure 5.2 and Figure 5.3.

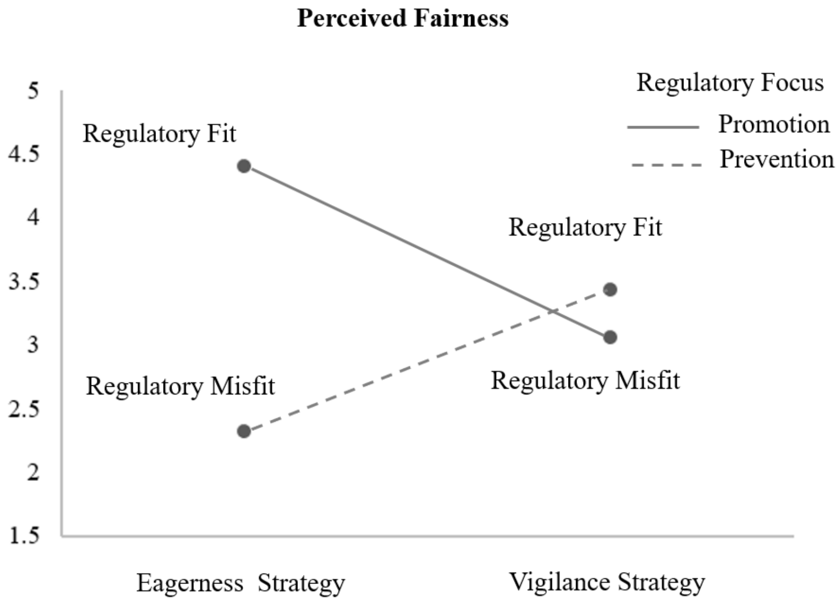

Figure 5.2 The effects of regulatory fit on perceived fairness.

Additionally, an independent sample t-test is conducted on the perceived fairness and social presence of the regulatory fit group and misfit group. The result is presented in Table 5.4. In terms of perceived fairness, groups in the regulatory fit condition ($M = 3.92$) significantly higher than groups in the regulatory misfit condition ($M = 2.69$, $t(134) = 8.84$, $p = 0.00$). Regarding perceived fairness, the results demonstrate groups in the regulatory fit condition ($M = 4.21$) significantly higher than groups in the regulatory misfit condition ($M = 3.35$, $t(134) = 6.04$, $p = 0.00$). Hence, H2a and H2b are all supported.

Table 5.4 Summary of independent samples test.

		t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference
PF	Equal variances assumed	8.837	134	.000	1.23	.13
	Equal variances not assumed	8.837	133.300	.000	1.23	.13
SP	Equal variances assumed	6.037	134	.000	.85	.141
	Equal variances not assumed	6.037	117.109	.000	.85	.14

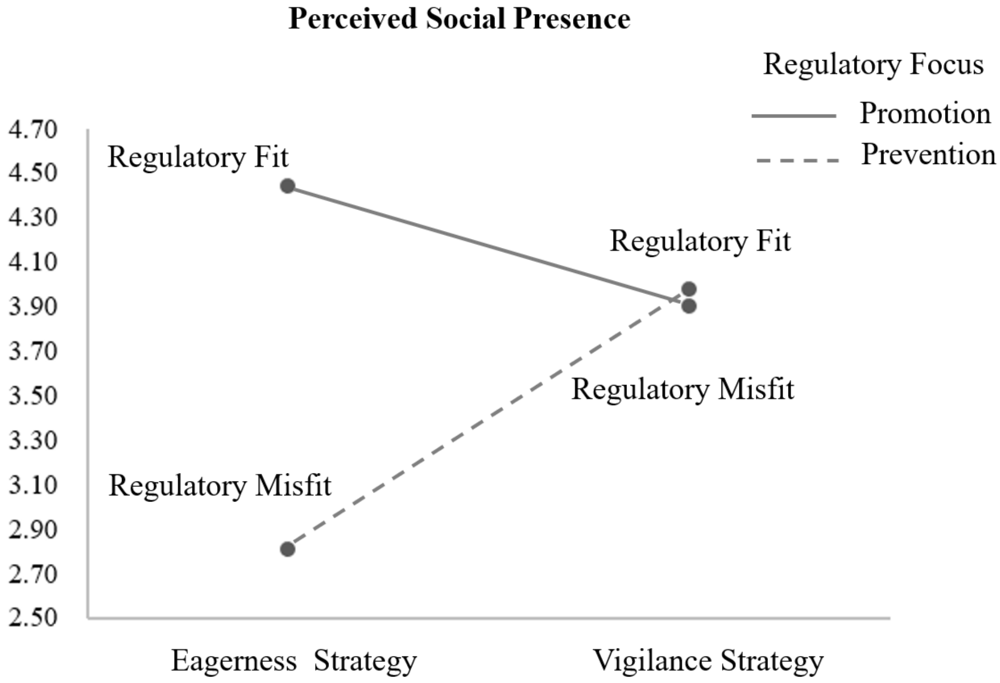

Figure 5.3 The effects of regulatory fit on perceived social presence.

5.6 Discussion

In this study, we extensively explore the psychological factors that influence job applicants' reactions and behavioral intentions, with a special focus on regulatory focus theory and regulatory fit in the context of AI-enabled interviews.

Firstly, job applicants with a promotion focus exhibit higher levels of perceived social presence and fairness perception compared to those with a prevention focus. Applicants with a promotion focus are driven by aspirations for advancement, growth, and achievement. They are more inclined to seek opportunities for gain and focus on the potential positive outcomes of their actions. In the context of AI-enabled interviews, these individuals may approach the interaction with optimism and confidence, leading to a heightened sense of social presence and fairness perception. Their emphasis on achieving goals and fulfilling aspirations may make them more attuned to positive cues in the interview process, fostering a sense of connection and fairness.

On the other hand, applicants with a prevention focus are motivated by concerns about avoiding loss, maintaining security, and preventing negative outcomes. They tend to be more vigilant and risk-averse, focusing on minimizing errors and maintaining stability. During the AI-enabled interview process, these individuals may exhibit heightened sensitivity to potential threats or biases in the interaction, leading to a more cautious and perhaps skeptical approach. This heightened vigilance may result in a lower sense of social presence and fairness perception as they may perceive the interview environment as more uncertain or potentially biased.

The motivational orientations of promotion and prevention focus shape how individuals perceive and respond to their environment, including interactions with AI interviewers, ultimately influencing their levels of social presence and fairness perception.

Furthermore, this research explored the roles of regulatory fit in the domain of AI-enabled interviews and found that regulatory fit significantly increases applicants' feelings of social presence and fairness during their interaction with an AI recruiter. Specifically, applicants who were prompted to consider their hopes and aspirations and then list eagerness means for goal pursuit (regulatory fit between promotion regulatory focus and eagerness goal pursuit strategy) felt stronger social presence and fairness than those who were prompted to think about hopes and aspirations and then enumerate vigilance means for goal pursuit. A similar pattern was found for the prevention regulatory focus condition.

For applicants who were prompted to consider their hopes and aspirations and then list eager means for goal pursuit, there is a regulatory fit between their promotion focus and the eager strategies they employ. Promotion-focused individuals are driven by aspirations for growth, advancement, and achievement. By adopting eager strategies that are aligned with their promotion focus, such as actively seeking opportunities and pursuing goals with enthusiasm, these applicants experience a sense of congruence between their motivational orientation and their approach to goal pursuit. As a result, they may feel more empowered and engaged during the interview process, leading to stronger perceptions of social presence and fairness. The regulatory fit between applicants' promotion focuses and their eager goal-pursuit strategies foster a sense of alignment and empowerment, enhancing their perceptions of social presence and fairness during the interview process.

6 Discussion

6.1 Conclusion

The field of applicant reactions, which emerged in the late 1980s and early 1990s, has been shaped by various influences such as business, ethical, technological, and scientific factors. This research has provided a comprehensive examination of various facets related to applicants' reactions to AI-enabled interviews, shedding light on the intricate dynamics that govern job applicant behavior during the AI-enabled interview process. Through a systematic analysis of factors influencing applicant reactions and behavioral intentions.

Firstly, this research presents an updated theoretical model of applicant reactions and empirically tests different aspects of this model through meta-analysis. The results highlight that applicants' reactions to AI-enabled interviews differ from FTF interviews. FTF interviews tend to elicit more positive behaviors due to their personal and engaging nature, fostering a connection with interviewers and a perception of dynamic responsiveness. Conversely, AI-enabled interview decreases organizational attractiveness due to perceived impersonality and mechanical interactions, raising concerns about personalized communication and engagement. Furthermore, applicant perceptions are correlated with various organizational attractiveness and behavioral intentions. A positive experience characterized by social presence and fairness can lead to more favorable attitudes toward the organization and an increased likelihood of positive behavioral intentions, such as accepting job offers and endorsing the company positively. This emphasizes the significance of creating engaging and empathetic interview experiences to enhance organizational outcomes.

Moreover, this research further analyzes the intricate relationship between social presence, perceived fairness, and behavioral intentions as well as how different combinations of attributes of AI-enabled interviews affect decision-making. This study confirms the significant impact of social presence and perceived fairness on job offer acceptance behavior, in line with Langer's findings (Langer, König et al. 2019, Langer, König et al. 2020, Roulin, Wong et al. 2022). Additionally, the research highlights the role of social bandwidth and interactivity in eliciting positive behavioral intentions, particularly in enhancing the inclination to accept job offers. Moreover, this study introduces the fsQCA method, which provides deeper insights into applicant behavior and demonstrates its efficacy in analyzing complex decision processes. Serving as a quantitative tool, the fsQCA enables a more precise examination of systemic changes in intricate environments, especially in unraveling the complexities of applicant reactions and behaviors. The findings underscore the pivotal role of social bandwidth, social presence, and interactivity as key attributes shaping applicant reactions during the AI-enabled interview process. These insights offer valuable implications for comprehending the mechanisms underlying the formation of an applicant's behavioral intentions and pave the way for future research in human resource management and organizational behavior.

Finally, this thesis highlights the significant influence of motivational orientation on job applicants' perceptions and reactions during AI-enabled interviews. Applicants with a promotion focus, characterized by aspirations for advancement and achievement, demonstrate higher levels of perceived social presence and fairness perception compared to those with a prevention focus, who are motivated by concerns about avoiding loss and maintaining security. Promotion-focused individuals approach interviews with optimism and confidence, emphasizing opportunities for gain and positive outcomes, thus fostering a sense of connection and fairness during the interview process. The research further explores the role of regulatory fit in enhancing applicants' experiences during AI-enabled interviews. It reveals that applicants who experience regulatory fit, where their promotion focus aligns with eager strategies for goal pursuit, report stronger feelings of social presence and fairness compared to those experiencing a mismatch between their motivational orientation and goal pursuit strategies. By understanding and leveraging these psychological factors, organizations can optimize the interview process to create a more positive and equitable experience for job applicants.

6.2 Contribution

This study sheds light on the nuanced dynamics of job applicants' reactions and behavioral intentions during AI-enabled interviews. Uncovering the underlying drivers of applicant reactions provides valuable insights into the applicant experience in this rapidly evolving AI-enabled recruitment landscape. This research has several theoretical contributions.

Firstly, this research has integrated previous literature and developed a theoretical model that bridges AI-enabled interviews, applicant perceptions, and applicant behavior. The findings fill the knowledge gap in existing studies by enhancing the understanding of applicant reactions and behavioral intentions. Additionally, this study confirms the viability of the mediating mechanism, assessing factors like fairness, trustworthiness, social presence, and anxiety. Perceived social presence and fairness emerge as the most influential factors in applicant behavior.

Furthermore, this research lays a foundational groundwork to address these fundamental queries. Additionally, it enriches the literature on AI-enabled interviews from job applicants' standpoint by integrating the social presence theory. By elucidating the intrinsic link between attributes of AI-enabled interviews and job offer acceptance intention, this study advances our comprehension of AI-enabled interview impact on applicants. This perspective is invaluable, shedding light on the psychological and emotional factors shaping applicants' reactions to AI recruiters.

Finally, the experiment successfully replicated the efficacy of regulatory focus and regulatory fit previously found across disciplines in the innovative domain of AI-enabled interviews within interactive virtual character, thus extending the realm of regulatory focus research beyond the traditional, noninteractive, thought-task paradigm. Ultimately, this research contributes to a deeper understanding of the human side of AI-enabled interviews and provides practical insights for organizations to optimize their recruitment strategies and enhance applicant experiences

This study also sheds light on some practical implications. The study sheds light on organizations and the direction for designing and implementing AI-enabled recruiting strategies. By examining the benefits and challenges of using AI-enabled interviews, the study offers several implications for organizations. Organizations should carefully consider whether to adopt AI-enabled interviews, as the results indicate that it may decrease the organization's attractiveness. Moreover, organizations should maintain oversight to ascertain whether AI-enabled interview leads to unexpected behavior such as self-selecting out of the interview process or rejecting the offer. This may occur for various reasons, including applicants' expectations of more interpersonal care from the organization, and negative experiences during the interview process. When an organization observes a decline in applicant engagement due to the use of AI-enabled interviews, it may be prudent to consider reverting to other interviews or exploring strategies for enhancing applicant experiences in AI-enabled interviews.

Furthermore, the study underscores the significance of considering the emotional and psychological aspects of the applicant experience when designing AI recruiter systems for providers. For instance, AI recruiters could be programmed to detect and respond to subtle cues in applicant responses, such as tone of voice or body language, to create a more empathetic and engaging interaction. By prioritizing features that promote positive emotional engagement, AI recruiter systems can enhance applicant perceptions and increase the likelihood of successful recruitment outcomes.

6.3 Limitations

While this study offers valuable insights into how attributes of AI-enabled interviews affect applicant behavior, it is important to acknowledge several limitations. Firstly, there is still much to uncover in the field of applicant reactions to AI-enabled interviews. Although the data from this meta-analysis provides a useful compilation of existing empirical findings, it should not be considered the definitive conclusion in this area. Critically, various aspects of the study rely on a limited number of studies, which becomes particularly evident when examining measurements separated over time. Additionally, some reported relationships are based on small sample sizes, preventing separate analyses based on factors like test type (e.g., cognitive ability tests vs. personality inventories). These factors could potentially influence the nature of the relationship between applicant reactions and organizational outcomes. Consequently, the existing body of evidence remains limited, making it challenging to draw definitive conclusions regarding the impact of applicant reactions on subsequent behaviors (Ryan and Ployhart 2000, LaHuis, MacLane et al. 2007, McCarthy, Bauer et al. 2017, Nikolaou, Georgiou et al. 2019).

Future research should further build upon existing studies that have explored applicant withdrawal intention (Ryan, Sacco et al. 2000, Truxillo, Bauer et al. 2002, Anderson, Salgado et al. 2010, Manroop, Malik et al. 2022). Organizations focused on applicant retention, particularly in retaining top applicants (as discussed by Murphy (1986) and Saks and Uggerslev (2010)), should assess how applicant reactions compare with other factors in explaining self-selection out of the interview stage. Additionally, there is a lack of studies examining the perceptions of applicants who opt out of the hiring process. Conducting longitudinal studies on the perceptions of applicants who become job incumbents would test Gilliland (1993) argument that initial impressions formed during the selection process may be associated with subsequent attitudes and behaviors on the job, including organizational citizenship behaviors, organizational commitment, and turnover.

Secondly, this research utilized a cross-sectional survey methodology, which, while efficient, may be susceptible to reply bias and self-selection bias. Although this method remains effective for researchers with limited resources (Yang, Yang et al. 2022), longitudinal data collection could offer advantages. Longitudinal studies would allow for tracking the evolution of applicants' attitudes and intentions towards AI-enabled interviews over time, offering a deeper understanding of their development. Additionally, applicants' perceptions are linked to various attitudes and intentions. However, only a limited number of studies have followed applicants into their job roles to explore potential spill-over effects on their performance (Gilliland 1994, Hunthausen 2000, Jordan, Wihler et al. 2019). To determine robust relationships between applicants' perceptions of the interview process and subsequent job performance, further research is needed to be conducted.

Finally, personal characteristics, including gender, personality traits, and beliefs, may act as moderators in the relationship among attributes, perceptions, and behavioral intention (Chen 2007, Sharma, Chen et al. 2012, Hwang and Griffiths 2017, Yang, Chen et al. 2020). Jin (2011) proposed that belief in a just world moderates the relationship between recruiter type (AI vs. Human) and applicants' behaviors. It was noted that individuals perceiving the world as less fair tend to have greater confidence in AI recruiters providing fair evaluations, leading to increased trust in AI assessments. Furthermore, this group expresses lower satisfaction with human recruiters, along with perceptions of unjust and unworthy behavior. Future research should further explore these individual differences, investigating the impact of variables such as personality traits and background on behavioral intentions. This approach will illuminate the diverse motivations and barriers encountered in the application of AI-enabled interviews. These identified limitations and proposed research directions pave the way for more comprehensive and globally applicable insights into understanding applicant behavior intention towards AI-enabled interviews.

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Appendices

Appendix A Supplementary Data of Meta-analysis

ID	Reference	Title	Study	Sample Size	Country/Region
1	Acikgoz, Y., et al. (2020)	Justice perceptions of artificial intelligence in selection	1	298	USA
			2	225	USA
2	Bankins, S., et al. (2022)	AI decision making with dignity? Contrasting workers' justice perceptions of human and AI decision-making in a human resource management context		446	USA
3	Basch, J. and K. Melchers (2019)	Fair and flexible?! Explanations can improve applicant reactions toward asynchronous video interviews		203	Germany
4	Basch, J. M., et al. (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		316	Germany
5	Basch, J. M., et al. (2020)	Smile for the camera! The role of social presence and impression management in perceptions of technology-mediated interviews		154	Germany
6	Basch, J. M., et al. (2021)	It takes more than a good camera: which factors contribute to differences between face-to-face interviews and videoconference interviews regarding performance ratings and interviewee perceptions?		114	Germany
7	Bauer, T. N., et al. (2004)	Applicant reactions to different selection technology: face-to-face, interactive voice response, and computer-assisted telephone screening interviews		153	USA

ID	Reference	Title	Study	Sample Size	Country/Region
8	Behrend, T., et al. (2012)	The effects of avatar appearance on interviewer ratings in virtual employment interviews		374	USA
9	Bill, B. and K. G. Melchers (2022)	Thou Shalt not Lie! Exploring and testing countermeasures against faking intentions and faking in selection interviews	2	213	Germany
10	Brenner, F. S., et al. (2016)	Asynchronous video interviewing as a new technology in personnel selection: the applicant's point of view		106	Germany
11	Chapman, D. S., et al. (2003)	Applicant reactions to face-to-face and technology-mediated interviews: a field investigation		802	Canada
12	Figueroa-Armijos, M., et al. (2022)	Ethical perceptions of AI in hiring and organizational trust: the role of performance expectancy and social influence		305	UK+US+Ireland +Canada
13	Folger, N., et al. (2021)	Applicant reactions to digital selection methods: a signaling perspective on innovativeness and procedural justice	1	475	Germany
			2	335	Germany
14	Harold, C. M., et al. (2015)	Investigating the effects of applicant justice perceptions on job offer acceptance	1	332	USA
			2	2974	USA
15	Hiemstra, A. M. F., et al. (2019)	Applicant perceptions of initial job candidate screening with asynchronous job interviews	1	160	USA

ID	Reference	Title	Study	Sample Size	Country/Region
16	Horn, R. and T. Behrend (2017)	Video killed the interview star: Does picture-in-picture affect interview performance?		113	USA
17	Horodyski, P. (2023)	Applicants' perception of artificial intelligence in the recruitment process		552	Global
18	Kaibel, C., et al. (2019)	Applicant perceptions of hiring algorithms - uniqueness and discrimination experiences as moderators	1	165	Germany
			2	255	Germany
19	Kleinlogel, E. P., et al. (2023)	"The interviewer is a machine!" Investigating the effects of conventional and technology-mediated interview methods on interviewee reactions and behavior		299	India, Swissland
20	Köchling, A., et al. (2022)	Can I show my skills? Affective responses to artificial intelligence in the recruitment process		160	Germany
21	Langer, M., et al. (2021)	Spare me the details: How the type of information about automated interviews influences applicant reactions		124	Germany
22	Langer, M., et al. (2019)	Highly-automated job interviews: Acceptance under the influence of stakes		123	Germany
23	Langer, M., et al. (2018)	Information as a double-edged sword: The role of computer experience and information on applicant reactions towards novel technologies for personnel selection		120	Germany
24	Langer, M., et al. (2020)	Is anybody listening? The impact of automatically evaluated job interviews on impression management and applicant reactions		124	Germany

ID	Reference	Title	Study	Sample Size	Country/Region
25	Langer, M., et al. (2017)	Examining digital interviews for personnel selection: Applicant reactions and interviewer ratings		113	Germany
26	Langer, M., et al. (2019)	Highly automated interviews: applicant reactions and the organizational context		148	Germany
27	Mccarthy, J. M., et al. (2021)	Distressed and distracted by COVID-19 during high-stakes virtual interviews: The role of job interview anxiety on performance and reactions		8343	Global
28	Muralidhar, S., et al. (2020)	Understanding applicants' reactions to asynchronous video interviews through self-reports and nonverbal cues		221	Switzerland
29	Newman, D. T., et al. (2020)	When eliminating bias isn't fair: Algorithmic reductionism and procedural justice in human resource decisions	2	1654	USA
			3	189	USA
			5	213	USA
30	Oostrom, J. K., et al. (2023)	Applicant reactions to algorithm - versus recruiter - based evaluations of an asynchronous video interview and a personality inventory	1	172	USA
			2	276	USA
31	Ötting, S. K. and G. W. Maier (2018)	The importance of procedural justice in Human-Machine Interactions: Intelligent systems as new decision agents in organizations	1	149	Germany
			2	145	Germany

ID	Reference	Title	Study	Sample Size	Country/Region
32	Pandey, S. and M. Bahukhandi (2022)	Applicants’ perception towards the application of AI in recruitment process		130	India
33	Roulin, N., et al. (2023)	Ready? Camera rolling… action! Examining interviewee training and practice opportunities in asynchronous video interviews	1	202	Canada
			2	156	Canada
34	Roulin, N., et al. (2022)	Is more always better? How preparation time and re-recording opportunities impact fairness, anxiety, impression management, and performance in asynchronous video interviews		175	Canada
35	Straus, S. G., et al. (2016)	The effects of videoconference, telephone, and face-to-face media on interviewer and applicant judgments in employment interviews		60	USA
36	Suen, H.-Y., et al. (2019)	Does the use of synchrony and artificial intelligence in video interviews affect interview ratings and applicant attitudes?		180	China
37	Suen, H.-Y. and K.-E. Hung (2023)	Building trust in automatic video interviews using various AI interfaces: Tangibility, immediacy, and transparency		152	China
38	Suen, H.-Y. and K.-E. Hung (2024)	Revealing the influence of AI and its interfaces on job candidates’ honest and deceptive impression management in asynchronous video interviews		152	China
39	Sylva, H. and S. T. Mol (2009)	E-Recruitment: A study into applicant perceptions of an online application system		1325	Europe

ID	Reference	Title	Study	Sample Size	Country/Region
40	van Esch, P., et al. (2021)	Job candidates' reactions to AI-enabled job application processes		532	USA
41	van Esch, P., et al. (2019)	Marketing AI recruitment: The next phase in job application and selection		532	USA
42	Wesche, J. S. and A. Sonderegger (2021)	Repelled at first sight? Expectations and intentions of job-seekers reading about AI selection in job advertisements	1	36	Germany
			2	55	Germany
			3	172	Germany

Appendix B Questionnaires

B.1 Questionnaire for Study 2

Demographic Information. Please circle a number that best describes yourself.

GENDER What is your gender? 1. Male 2. Female

AGE How old are you? ____________.

EDU What is the highest level of education you have completed?

1. High school diploma or less
2. Associate degree or professional certificate after high school
3. Bachelor's degree
4. Master' degree
5. PHD
6. Other

INCOME What is your approximate annual income level before taxes?

1. Less than $30,000 2. $30,001--$50,000 3. $50,001--$100,000 4. $100,001 and over

WORK Do you work? 1. Yes. 2. No

Interview Experience Do you have interview experience?

1. Yes. 2. No

Interaction Experience Do you have experience of AI-enabled interview?

1. Yes. 2. No

Interaction Experience Do you have experience of interaction with AI?

1. Yes. 2. No

Scale	Item	Strongly Disagree	Slightly Disagree	Neutral	Slightly Agree	Strongly Agree
Job Offer Acceptance	I would accept the job if it was offered to me.					
	This is the job I want.					

	Based on my experience with this interview process, it would be great if I could work for the company.					
Perceived Social Presence	I think that using an AI recruiter during the interview process will provide me with a sense of human contact.					
	I think that using an AI recruiter during the interview process will provide me with a sense of sociability.					
	I think that using an AI recruiter during the interview process will provide me with a sense of human warmth.					
Perceived Fairness	I think that using an AI recruiter during the interview process was a neutral way to select people.					
	I think that using an AI recruiter during the interview process was an unbiased way to select people.					
	All things considered, I feel the interview process was fair.					
Transparency	I feel that using an AI-enabled recruitment process is transparent.					
	I feel it is obvious what the AI-enabled recruitment process is measuring.					
Interactivity	I feel an AI recruiter would facilitate enough communication during the interview.					
	I would have felt comfortable asking questions about the interview if I had any.					
	I am sure that I was in control of the interview.					
	Through my performance, I could influence the result of the interview.					

	I feel that using an AI recruiter during the interview process would be effective and efficient.					
	Overall, I feel an AI-enabled interview would be highly interactive.					
Social Bandwidth	I think that the AI recruiter would have human-like characteristics.					
	I think that the avatar or the voice of the AI recruiter would be like a human.					
	I think that the speaking style of an AI recruiter would be like human beings.					
Privacy Concern	In such an interview, it is important to me to keep my privacy intact.					
	In such an interview, I am concerned about my privacy.					
	Such interviews threaten applicants' privacy. (I think novel technologies are threatening privacy increasingly.)					
	During this interview, I provided private data that will be stored safely.					

B.2 Questionnaire for Study 3

Please circle a number that best describes yourself.

No.	Item	Never or Seldom—>Very often				
1	Compared to most people, are you typically unable to get what you want out of life?	1	2	3	4	5
2	Growing up, would you ever "cross the line" by doing things that your parents would not tolerate?	1	2	3	4	5
3	How often have you accomplished things that got you "psyched" to work even harder?	1	2	3	4	5
4	Did you get on your parents' nerves often when you were growing up?	1	2	3	4	5
5	How often did you obey rules and regulations that were established by your parents?	1	2	3	4	5
6	Growing up, did you ever act in ways that your parents thought were objectionable?	1	2	3	4	5
7	Do you often do well at different things that you try?	1	2	3	4	5
8	When it comes to achieving things that are important to me, I find that I don't perform as well as I ideally would like to do.	1	2	3	4	5
9	I feel like I have made progress toward being successful in my life.	1	2	3	4	5
10	I have found very few hobbies or activities in my life that capture my interest or motivate me to put effort into them.	1	2	3	4	5

Demographic Information. Please circle a number which best describes yourself.

GENDER What is your gender? 1. Male 2. Female

AGE How old are you? ____________.

EDU What is the highest level of education you have completed?

7. High school diploma or less
8. Associate degree or professional certificate after high school
9. Bachelor’s degree
10. Master’ degree
11. PhD
12. Other

INCOME What is your approximate annual income level before taxes?

1. Less than $30,000 2. $30,001--$50,000 3. $50,001--$100,000 4. $100,001 and over

Do you work? 1. Yes. 2. No.

Do you have interview experience? 1. Yes. 2. No.

Do you have experience of AI-enabled interviews? 1. Yes. 2. No.

Do you have experience of interaction with AI? 1. Yes. 2. No.

Scale	Item	Strongly Disagree	Slightly Disagree	Neutral	Slightly Agree	Strongly Agree
Job Offer Acceptance	I would accept the job if it was offered to me.					
	This is the job I want.					
	Based on my experience with this interview process, it would be great if I could work for the company.					
Perceived Social Presence	I think that using an AI recruiter during the interview process will provide me with a sense of human contact.					
	I think that using an AI recruiter during the interview process will provide me with a sense of sociability.					
	I think that using an AI recruiter during the interview process will provide me with a sense of human warmth.					

Perceived Fairness	I think that using an AI recruiter during the interview process was a neutral way to select people.					
	I think that using an AI recruiter during the interview process was an unbiased way to select people.					
	All things considered, I feel the interview process was fair.					