

Article

Beyond Fairness: Authenticity in AI Interview Systems

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Abstract: This study examines how the characteristics of AI interview systems influence job seekers' perceptions and attitudes in the context of AI-based recruitment. While previous studies have mainly emphasized efficiency, fairness, and algorithmic bias, this study extends the discussion by contextualizing perceived authenticity as an important psychological perception in AI-mediated interview contexts. In this study, perceived authenticity refers to the extent to which job seekers perceive an AI interview system as a formal, reasonable, and credible recruitment procedure rather than as a merely mechanical or superficial assessment tool. Drawing on organizational justice theory and fairness heuristic theory, this study investigates how transparency, consistency, explainability, and controllability affect job seekers' perceived fairness and perceived authenticity, and how these perceptions influence organizational attractiveness. To test the proposed research model, survey data were collected from 409 Chinese job seekers with prior experience in AI interviews and analyzed using partial least squares structural equation modeling. The results indicate that transparency, consistency, explainability, and controllability all have significant positive effects on perceived fairness. Regarding perceived authenticity, transparency, explainability, and controllability show significant positive effects, whereas consistency has no significant effect. These findings suggest that stable and uniform system operation alone may not be sufficient for job seekers to perceive an AI interview system as credible, reasonable, or human-centered. In addition, both perceived fairness and perceived authenticity positively influence organizational attractiveness. This study contributes to AI recruitment research by extending and contextualizing the concept of perceived authenticity within AI-driven recruitment settings, clarifying how AI interview system characteristics shape applicants' evaluations of organizations.

Keywords: AI-based recruitment; transparency; consistency; explainability; controllability; applicant perception; procedural justice

1. Introduction

As human resource management research continues to evolve, recruitment and selection remain important areas for understanding how organizations attract and evaluate human capital (Fang, 2025). Artificial intelligence has increasingly transformed recruitment and selection practices, as AI-based recruitment tools are now used across multiple stages of hiring, including applicant sourcing, resume screening, video interviews, and decision-making support (Vrontis et al., 2023; Tursunbayeva et al., 2025). Recent research in human resource management has also emphasized that AI-related competencies and digital human capital are becoming important issues in human resource development (Lu and Mohamad Said, 2025). This transformation is particularly meaningful in China, where the recruitment system has experienced a gradual shift from state-led job allocation to market-oriented hiring, legal regulation, competency-based selection, and digitally supported recruitment practices.

The development of China's recruitment system reflects a broader transition toward more open, standardized, and technology-mediated hiring procedures, as shown in **Figure 1**. Against this background, AI interview systems represent a recent stage in the digital transformation of recruitment, in which algorithmic technologies are used to collect and analyze applicants' interview responses and support interview evaluation. Compared with traditional face-to-face interviews, AI interview systems can improve recruitment efficiency and standardize evaluation procedures, but they also create uncertainty for job seekers because the criteria, logic, and processes of algorithmic evaluation are often difficult to observe directly (Langer et al., 2019; Hunkenschroer and Luetge, 2022; Köchling and Wehner, 2020).

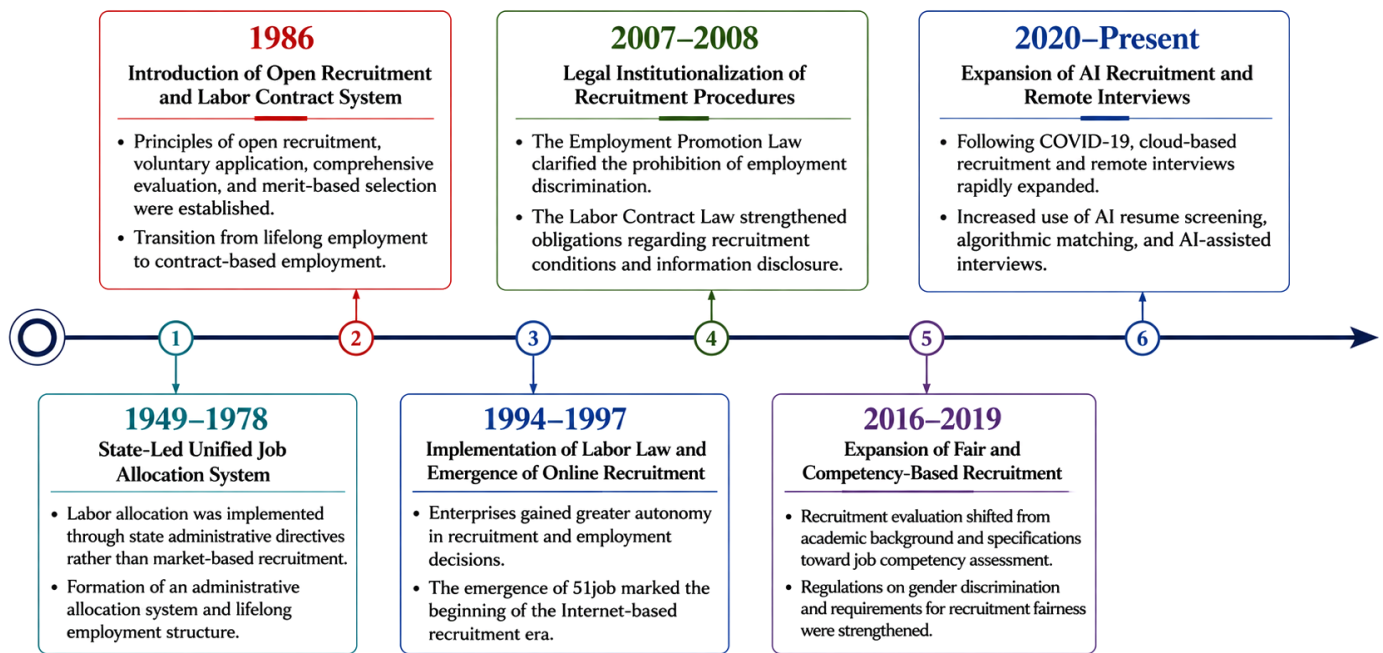


Figure 1. Major Events Related to Changes in China's Recruitment System

In recruitment contexts, job seekers do not evaluate an organization only through final selection outcomes; rather, they form attitudes toward the organization based on how fair, reasonable, and acceptable the selection procedure appears to be (Gilliland, 1993; Lavanchy et al., 2023). Therefore, understanding how job seekers perceive AI interview systems is important for explaining their reactions to AI-mediated recruitment procedures.

Organizational justice theory provides a useful foundation for explaining applicants' evaluations of AI interview systems. From the perspective of procedural justice, individuals judge the fairness of a decision-making procedure based on factors such as consistency, sufficient information, explainability, and opportunities for voice or correction (Greenberg, 1987; Leventhal, 1980; Colquitt et al., 2001). In AI interview contexts, transparency, consistency, explainability, and controllability can therefore be understood as important system characteristics that shape job seekers' perceived fairness (Schnackenberg and Tomlinson, 2016; Doshi-Velez and Kim, 2017). In addition, fairness heuristic theory suggests that when individuals face uncertain situations and cannot fully understand the internal logic of a decision-making system, they rely on fairness-related cues to judge whether the system is trustworthy, legitimate, and acceptable (Lind, 2001; Lind and Van den Bos, 2002).

Although previous studies on AI-based recruitment have examined algorithmic bias, ethical risks, recruitment efficiency, and procedural fairness, limited research has investigated how specific characteristics of AI interview systems jointly influence perceived fairness, perceived authenticity, and organizational attractiveness (Rigotti and Fosch-Villaronga, 2024; Horodyski, 2023; Babaee and Shank, 2025; Luo et al., 2025). The purpose of this study is to examine how AI interview system characteristics influence job seekers' perceived fairness, perceived authenticity, and organizational attractiveness. To achieve this purpose, this study classifies AI interview system characteristics into transparency, consistency, explainability, and controllability, and tests the proposed research model using survey data collected from 409 Chinese job seekers with AI interview experience and partial least squares structural equation modeling.

2. Theoretical Framework and Literature Review

2.1. Organizational Justice Theory

Organizational justice theory explains how individuals evaluate the fairness of organizational decisions, procedures, and interactions (Greenberg, 1987). In recruitment and selection contexts, applicants evaluate not only the final hiring outcome but also whether the selection procedure is reasonable, consistent, and legitimate (Gilliland, 1993). Procedural justice is particularly relevant to selection systems because applicants form fairness judgments based on how evaluation criteria are applied and how the decision-making process is conducted (Colquitt, 2001). Previous applicant reaction research also shows that perceived fairness in selection procedures can influence applicants' attitudes toward the organization and their subsequent behavioral intentions (Hausknecht et al., 2004).

In AI interview contexts, organizational justice theory is useful because the evaluation process is partly mediated by a technological system rather than being conducted only by human interviewers (Acikgoz et al., 2020). Since applicants may not directly observe how an AI interview system collects, processes, and evaluates their responses, procedural characteristics become important cues for fairness judgments (Köchling and Wehner, 2020). Based on procedural justice logic, this study identifies transparency, consistency, explainability, and controllability as key characteristics of AI interview systems that may shape applicants' perceived fairness (Leventhal, 1980). Therefore, organizational justice theory provides the theoretical foundation for examining how these four system characteristics influence job seekers' fairness perceptions in AI-mediated interview procedures (Gilliland, 1993).

2.2. Fairness Heuristic Theory

Fairness heuristic theory explains how individuals use fairness information as a cognitive shortcut when they face uncertainty in organizational decision-making situations (Lind, 2001). When individuals cannot fully know the decision-maker's intention or the accuracy of a decision outcome, they tend to rely on procedural fairness cues to judge whether an authority, institution, or system is trustworthy and acceptable (Lind and Van den Bos, 2002). This theory is especially relevant to AI interview systems because applicants often cannot fully understand the internal logic, algorithmic evaluation criteria, or data-processing process of the system (Jones and Martens, 2009). Under conditions of uncertainty, individuals often rely on fairness-related cues to evaluate whether an authority or decision system is trustworthy and legitimate (Tyler, 1989). In organizational and technology-mediated contexts, procedural fairness has been shown to shape trust, acceptance, and perceived

legitimacy (van den Bos, 2001). In AI interview settings, where applicants cannot directly observe the system's internal logic, fairness perceptions may therefore serve as an important basis for judging whether the system is authentic and appropriate for recruitment purposes.

In AI interview contexts, fairness perceptions may influence not only whether applicants regard the procedure as fair but also whether they perceive the system as credible, legitimate, and suitable for a formal recruitment process (Lind and Van den Bos, 2002). Perceived fairness can therefore serve as an important psychological basis for perceived authenticity, because applicants may use fairness cues to judge whether the AI interview system is a genuine and responsible recruitment procedure (Jones and Martens, 2009). Accordingly, fairness heuristic theory provides the theoretical foundation for explaining the relationship between perceived fairness and perceived authenticity in this study.

2.3. AI-Based Recruitment and AI Interview Systems

AI-based recruitment refers to the use of artificial intelligence technologies across different stages of the hiring process, including applicant sourcing, resume screening, interview support, assessment, and decision-making assistance (Budhwar et al., 2022). AI interview systems are a specific form of AI-based recruitment used in the interview stage to collect, process, and analyze applicants' interview responses and support evaluation-related decisions (Tasheva and Karpovich, 2024). In this study, an AI interview system is defined as a recruitment-related information system that uses AI technologies to support the evaluation of job seekers' interview responses (Acikgoz et al., 2020).

AI interview systems differ from traditional face-to-face interviews because the presentation of questions, recording of responses, data processing, and evaluation support are mediated by algorithmic logic (Kellogg et al., 2020). These systems are often implemented as asynchronous video interviews or structured digital interviews in which applicants respond to system-generated questions through video or audio within a limited time (Lukacik et al., 2022). AI interview systems may improve procedural standardization by applying similar questions and evaluation criteria across applicants (Dunlop et al., 2025). However, because applicants may not fully understand how their responses are evaluated, AI interview systems can also create uncertainty and fairness concerns (Köchling and Wehner, 2020). Therefore, AI interview systems should be understood not only as tools for improving recruitment efficiency but also as important recruitment experiences that shape applicants' perceptions of the organization (Horodyski, 2023).

2.4. AI Interview System Characteristics and Perceived Fairness

Transparency refers to the extent to which a system clearly provides information about evaluation criteria, procedures, and the use of applicant data (Lepri et al., 2018). In AI interviews, transparency helps applicants understand what information is collected, how their responses are evaluated, and how evaluation results are generated (Newman et al., 2020). When evaluation information is not sufficiently provided, applicants may perceive the AI interview process as opaque and difficult to accept (Martin and Waldman, 2023). Therefore, transparency can strengthen procedural legitimacy and perceived fairness in AI-mediated selection procedures (Schnackenberg and Tomlinson, 2016).

Consistency refers to the extent to which the same evaluation criteria and procedures are applied stably across different applicants and situations (Derous et al., 2004). In selection procedures, consistency is an important condition of procedural fairness because

applicants expect to be evaluated according to the same standards (Bauer et al., 2001). AI interview systems may enhance consistency by applying standardized questions and evaluation rules, but this advantage contributes to fairness only when applicants perceive the criteria as stable and reasonable (Zhang and Yencha, 2022).

Explainability refers to the extent to which an AI system can provide understandable explanations for its judgment process and evaluation results (Doshi-Velez and Kim, 2017). In AI interview contexts, explainability is important because applicants may not know why a particular evaluation result was produced (Mittelstadt et al., 2019). Providing understandable explanations can reduce uncertainty and increase applicants' perceptions that the evaluation process is reasonable and acceptable (Schoeffer et al., 2022). In recruitment contexts, explainable evaluation procedures can therefore support applicants' perceptions of procedural fairness (Lee, 2018).

Controllability refers to the extent to which applicants perceive that they can express opinions, provide feedback, correct errors, or challenge evaluation results during or after the selection process (Bies and Shapiro, 1988). Procedural justice research suggests that people are more likely to accept a decision-making procedure as fair when they have voice or correction opportunities (Leventhal, 1980). In AI interview systems, controllability can reduce the perception that automated evaluation is one-sided and uncontestable (Potosky, 2008). Recent research on AI-driven recruitment also emphasizes the importance of contestability and applicant participation in automated hiring systems (Hadžic et al., 2025).

Based on the above discussion, the following hypotheses are proposed:

H1a: Transparency positively influences perceived fairness.

H2a: Consistency positively influences perceived fairness.

H3a: Explainability positively influences perceived fairness.

H4a: Controllability positively influences perceived fairness.

2.5. AI Interview System Characteristics and Perceived Authenticity

Perceived authenticity refers to the extent to which job seekers perceive an AI interview system as genuine, sincere, and aligned with the intended purpose of recruitment rather than as a purely mechanical or superficial assessment tool. (Enli, 2015). Authenticity is a subjective judgment about whether a target is real, trustworthy, and consistent with its intended purpose (Morhart et al., 2015). Unlike trust, which reflects a willingness to be vulnerable based on expectations of competence and benevolence (Mayer et al., 1995), or credibility and legitimacy, which emphasize competence, reliability, and rightful authority, authenticity focuses on the perceived congruence between expressed intentions and actual motives (Van den Bos et al., 2001), as well as the absence of performative deception. In AI-driven interview contexts, perceived authenticity therefore captures applicants' impressions that the system's interactions are sincere and aligned with the purpose of fair evaluation rather than merely procedural or instrumental. Consequently, an AI interview system may be viewed as competent and reliable while simultaneously being perceived as inauthentic if its responses appear overly mechanical, scripted, or detached from human norms of sincerity. This distinction highlights authenticity as a unique psychological response to AI-mediated recruitment processes that is conceptually distinct from trust and credibility. In digital service and AI-based interaction contexts, perceived authenticity has been used to explain how users evaluate whether a technology-mediated experience feels credible and meaningful (Alimamy and Kuhail, 2023).

In AI interview contexts, transparency may enhance perceived authenticity because clear information about evaluation criteria and procedures helps applicants

understand the purpose and operation of the system (Schnackenberg and Tomlinson, 2016). Consistency may support perceived authenticity because stable evaluation standards can signal that the system follows a formal and structured recruitment procedure (Bauer et al., 2001). Explainability may strengthen perceived authenticity because understandable explanations help applicants perceive the system as reasonable rather than as a black-box evaluation tool (Doshi-Velez and Kim, 2017). Controllability may also enhance perceived authenticity because opportunities for feedback or correction can make the AI interview procedure appear more responsible and applicant-centered (Bies and Shapiro, 1988).

Previous studies suggest that perceived authenticity is important in technology-mediated contexts because users evaluate not only functional performance but also whether the system appears credible, responsible, and aligned with its intended purpose (Vo et al., 2025). In recruitment contexts, when an AI interview system provides clear information, stable standards, understandable explanations, and feedback opportunities, applicants may be more likely to perceive it as a formal and legitimate recruitment procedure (Deephhouse et al., 2017). Therefore, AI interview system characteristics are expected to positively influence job seekers' perceived authenticity.

Based on the above discussion, the following hypotheses are proposed:

H1b: Transparency positively influences perceived authenticity.

H2b: Consistency positively influences perceived authenticity.

H3b: Explainability positively influences perceived authenticity.

H4b: Controllability positively influences perceived authenticity.

2.6. Perceived Authenticity

Recently, digital authenticity has emerged as an important research topic across multiple disciplines, including digital media, AI services, virtual environments, and human-computer interaction. Recent bibliometric and literature review studies have shown that authenticity is increasingly discussed as a multidimensional concept associated with trust, legitimacy, transparency, and user perception (Chen et al., 2025; Choi et al., 2025). Building upon this emerging stream of research, the present study contextualizes perceived authenticity within AI interview systems.

Perceived fairness refers to the extent to which job seekers perceive the AI interview procedure and evaluation process as fair, reasonable, and legitimate (Colquitt, 2001). In recruitment research, fairness perceptions are important psychological responses because they influence applicants' acceptance of selection procedures and their evaluations of organizations (Hausknecht et al., 2004). In AI-based recruitment, applicants evaluate not only the technical accuracy of the system but also whether they are assessed in a justifiable and respectful manner (Lavanchy et al., 2023). Therefore, perceived fairness can be regarded as an important psychological perception formed through applicants' interaction with AI interview systems (Babae and Shank, 2025).

According to fairness heuristic theory, people use fairness information to judge whether a system or authority is trustworthy when they cannot fully understand the decision-making process (Lind and Van den Bos, 2002). In AI interview contexts, applicants may use perceived fairness as a cue to judge whether the system is credible, reasonable, and suitable for formal recruitment (Jones and Martens, 2009). Therefore, when applicants perceive the AI interview procedure as fair, they are more likely to perceive the system as authentic and acceptable.

Based on the above discussion, the following hypothesis is proposed:

H5: Perceived fairness positively influences perceived authenticity.

2.7. Organizational Attractiveness

Organizational attractiveness refers to the extent to which job seekers perceive a particular organization as a desirable employer and develop positive interest in working for that organization (Highhouse et al., 2003). In recruitment research, organizational attractiveness is closely related to applicant attraction, job pursuit intention, and employer image (Lievens and Highhouse, 2003). Applicants often infer an organization's values and attitudes from the recruitment procedures they experience (Chapman et al., 2005). Therefore, applicants' perceptions of AI interview systems may extend beyond the evaluation procedure and influence their overall evaluation of the recruiting organization (Luo et al., 2025).

Perceived fairness can enhance organizational attractiveness because a fair selection procedure signals that the organization treats applicants in a reasonable and respectful way (Hausknecht et al., 2004). Perceived authenticity can also enhance organizational attractiveness because applicants who regard the AI interview system as a credible and formal recruitment procedure may evaluate the organization more positively (Enli, 2015). Recent studies on AI-enabled hiring also show that procedural justice perceptions in AI recruitment are closely related to organizational attraction and application-related attitudes (Babaei and Shank, 2025). Therefore, perceived fairness and perceived authenticity are expected to positively influence organizational attractiveness.

Based on the above discussion, the following hypotheses are proposed:

H6: Perceived fairness positively influences organizational attractiveness.

H7: Perceived authenticity positively influences organizational attractiveness.

3. Research Framework

Based on organizational justice theory and fairness heuristic theory, this study develops a research framework to examine the relationships among AI interview system characteristics, perceived fairness, perceived authenticity, and organizational attractiveness. Specifically, transparency, consistency, explainability, and controllability are proposed as key characteristics of AI interview systems that influence job seekers' perceived fairness and perceived authenticity. In addition, perceived fairness is expected to affect perceived authenticity, and both perceived fairness and perceived authenticity are expected to enhance organizational attractiveness. The proposed research framework is presented in **Figure 2**.

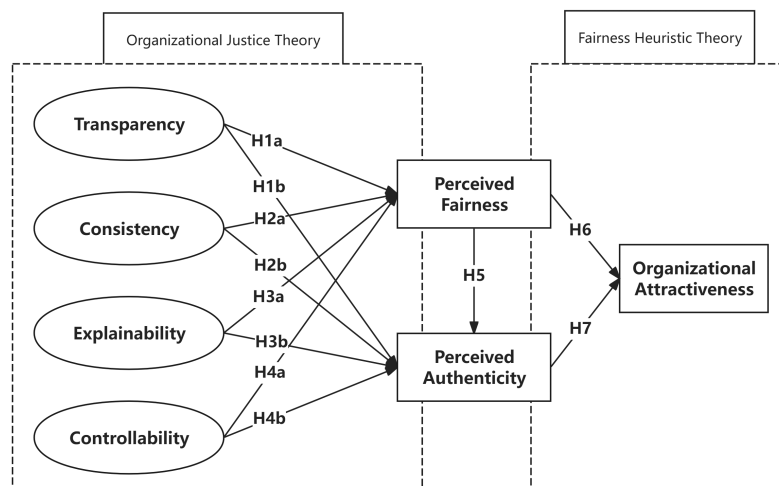


Figure 2. Research framework.

4. Methodology

4.1. Research Design

This study adopted a quantitative research design to examine the structural relationships among AI interview system characteristics, perceived fairness, perceived authenticity, and organizational attractiveness. The purpose of the empirical analysis was to test whether transparency, consistency, explainability, and controllability influence job seekers' perceived fairness and perceived authenticity, and whether these perceptions subsequently affect organizational attractiveness. Because the research model includes multiple latent variables and several hypothesized paths, a survey-based approach was considered appropriate for collecting standardized responses from job seekers with AI interview experience.

4.2. Sample and Data Collection

The target respondents of this study were Chinese job seekers who had prior experience with AI interviews. This sample was selected because the study aims to analyze how job seekers' perceptions of AI interview system characteristics influence their perceived fairness, perceived authenticity, and organizational attractiveness. Data were collected through Credamo, a Chinese online survey platform, from January 5 to January 22, 2025. Before participating in the survey, respondents were informed of the research purpose and the content of the questionnaire. A total of 450 questionnaires were collected. After excluding incomplete, insincere, and unsuitable responses, 409 valid responses were used for the final empirical analysis.

4.3. Measurement of Variables

The questionnaire was developed based on the major constructs in the proposed research model. The measurement variables included transparency (TR), consistency (CO), explainability (EX), controllability (CT), perceived fairness (PF), perceived authenticity (PA), and organizational attractiveness (OA). All constructs were operationally defined in the context of AI interview systems, and the measurement items were adapted from prior studies. Each item was measured using a five-point Likert scale, ranging from 1 = strongly disagree to 5 = strongly agree. The operational definitions and measurement sources of the variables are presented in **Table 1**.

Table 1. Operational definitions and measurement sources

Construct	Operational Definition	Sources
TR	The extent to which job seekers perceive that the AI interview system voluntarily discloses evaluation criteria, decision-making processes, and data-use information, and presents such information in a clear and accurate manner. This construct is measured based on the sufficiency and understandability of information disclosure.	Schnackenberg & Tomlinson(2016)
CO	The extent to which job seekers perceive that the AI interview system applies the same evaluation criteria and stable rules to different applicants. This construct is measured based on perceptions of uniform evaluation standards and procedural stability.	Colquitt(2001) Wesche(2021)
EX	The extent to which job seekers perceive that the AI interview system can explain its evaluation logic and decision-making basis in a human-understandable way. This construct is measured based on the understandability of the evaluation process and the clarity of explanations.	Doshi-Velez & Kim(2017)

Continuation Table:

Construct	Operational Definition	Sources
CT	The extent to which job seekers perceive that they have opportunities to raise objections, provide feedback, or request correction or supplementation regarding the AI interview evaluation process or results. This construct is measured based on perceived participation and correction opportunities in the procedure.	Hilliard et al. (2022)
PF	The extent to which job seekers perceive that the procedures applied by the AI interview system in making evaluation decisions are fair and reasonable. This construct is assessed based on subjective perceptions of procedural fairness and the legitimacy of the decision-making process.	Colquitt(2001) Lepri(2018)
PA	The extent to which job seekers perceive the AI interview system as a real, legitimate, and trustworthy formal recruitment procedure. This construct is assessed based on subjective psychological perceptions of the system's credibility, legitimacy, and authenticity.	Morhart(2015) Napoli(2014)
OA	The extent to which job seekers positively evaluate and prefer a specific organization as a future place of employment. This construct is assessed based on overall favorability toward the organization and intention to work for the organization.	Highhouse et al. (2003); Babae &Shank (2025)

4.4. Data Analysis Method

The collected data were analyzed using SPSS 27.0 and SmartPLS 4.0. First, SPSS 27.0 was used to examine the demographic characteristics of the sample and to conduct basic statistical analyses. Then, SmartPLS 4.0 was used to test the measurement model and structural model through partial least squares structural equation modeling. The measurement model was evaluated using reliability and validity indicators, including Cronbach's alpha, composite reliability, average variance extracted, and factor loadings. Discriminant validity was assessed using the HTMT ratio and the Fornell-Larcker criterion. In addition, multicollinearity was examined using variance inflation factor values, and the structural model was tested through path analysis. PLS-SEM was selected because it is suitable for analyzing complex relationships among multiple latent variables and is relatively flexible regarding sample size and distributional assumptions.

5. Data Analysis and Results

5.1. Demographic Characteristics

The demographic characteristics of the respondents are presented in **Table 2**. A total of 409 valid responses were used for the final analysis. The sample included both male and female respondents, with females accounting for a slightly higher proportion. Most respondents were in their twenties or younger, and the majority had junior college or bachelor's degree-level education. In terms of job-seeking status, the sample included first-time job seekers, re-employment seekers, students preparing for employment or internships, currently employed individuals seeking job-changing opportunities, and unemployed respondents actively seeking jobs. Regarding AI interview experience, more than half of the respondents had participated in AI interviews one to two times. Overall, the demographic profile indicates that the sample was appropriate for examining job seekers' perceptions of AI interview systems.

Table 2. Demographic Characteristics of the Sample (n = 409)

Category		Frequency	Percentage (%)
Gender	Male	196	47.92
	Female	213	52.08
Age	20 or below	125	30.56
	20s	128	31.30
	30s	75	18.34
	40s	45	11.00
	50 or above	36	8.80
Education Level	High school or below	77	18.83
	Junior college	171	41.81
	Bachelor's degree	117	28.61
	Master's program	22	5.38
	Doctoral program	22	5.38
Employment Status	First-time job seeking	170	41.56
	Re-employment	239	58.44
Current Job-Seeking Status	Student preparing for internship or employment	169	41.32
	Currently employed and seeking job-changing opportunities	55	13.45
	Currently unemployed and actively seeking employment	171	41.81
	Other	14	3.42
Number of AI Interview Experiences Before Survey Participation	1–2 times	234	57.21
	3–5 times	109	26.65
	6 times or more	66	16.14
Familiarity with AI Products and New Technologies	Not familiar at all	25	6.11
	Not familiar	54	13.20
	Neutral	155	37.90
	Familiar	98	23.96
	Very familiar	77	18.83

5.2. Measurement Model Assessment

The measurement model was assessed by examining internal consistency reliability, convergent validity, and indicator reliability. In PLS-SEM research, Cronbach's alpha and composite reliability values above 0.70 generally indicate acceptable internal consistency reliability, while AVE values above 0.50 indicate adequate convergent validity (Sarstedt et al., 2021). As shown in **Table 3**, all Cronbach's alpha and composite reliability values exceeded the recommended threshold of 0.70, and all AVE values were above 0.50. In addition, as presented in

Table 4, all factor loadings exceeded the acceptable threshold. These results indicate that the measurement model demonstrated satisfactory reliability, convergent validity, and indicator reliability.

Table 3. Reliability and Validity Assessment

	Cronbach's alpha	Composite reliability(CR)	Average variance extracted (AVE)
TR	0.880	0.918	0.736
CO	0.874	0.914	0.725
CT	0.832	0.899	0.749
EX	0.885	0.920	0.743
PF	0.884	0.915	0.683
PA	0.864	0.907	0.710
OA	0.877	0.911	0.671

Table 4. Factor Loadings

	PF	PA	EX	TR	CO	CT	OA
PF1	0.826						
PF2	0.81						
PF3	0.831						
PF4	0.834						
PF5	0.831						
PA1		0.818					
PA2		0.867					
PA3		0.839					
PA4		0.845					
EX1			0.862				
EX2			0.872				
EX3			0.854				
EX4			0.859				
TR1				0.864			
TR2				0.839			
TR3				0.866			
TR4				0.862			
CO1					0.847		
CO2					0.87		
CO3					0.849		

Continuation Table:							
	PF	PA	EX	TR	CO	CT	OA
CO4					0.84		
CT1						0.863	
CT2						0.882	
CT3						0.851	
OA1							0.837
OA2							0.813
OA3							0.816
OA4							0.806
OA5							0.823

5.3 Common Method Bias Assessment

To assess potential common method bias (CMB), we first conducted Harman's single factor test; the first factor accounted for only 30.893% of the total variance. In addition, because our analysis employed PLS SEM, we examined collinearity using Kock's (2015) full collinearity assessment: all construct/path VIFs ranged from 1.395 to 1.716, well below commonly used cutoffs (3.3 or 5). Taken together, these findings indicate that common method bias is unlikely to pose a serious threat to the conclusions of this study.

5.4. Discriminant Validity

Discriminant validity was examined using the heterotrait-monotrait ratio of correlations and the Fornell-Larcker criterion. The HTMT criterion is widely used to assess discriminant validity in variance-based structural equation modeling, and values below 0.90 are generally considered acceptable (Henseler et al., 2015). As shown in **Table 5**, all HTMT values were below the recommended threshold, indicating that the constructs were sufficiently distinct from one another.

The Fornell-Larcker criterion was also applied to further assess discriminant validity. According to this criterion, the square root of each construct's AVE should be greater than its correlations with other constructs (Fornell and Larcker, 1981). As presented in **Table 6**, the diagonal values were higher than the corresponding inter-construct correlations. Therefore, the results confirm that discriminant validity was established.

Table 5. Discriminant Validity Assessment: HTMT Criterion

	CO	CT	EX	PF	PA	OA	TR
CO							
CT	0.58						
EX	0.545	0.504					
PF	0.56	0.555	0.594				

Continuation Table:

	CO	CT	EX	PF	PA	OA	TR
PA	0.506	0.584	0.552	0.607			
OA	0.598	0.624	0.57	0.668	0.681		
TR	0.53	0.603	0.537	0.576	0.551	0.652	

Table 6. Discriminant Validity Assessment: Fornell-Larcker Criterion

	CO	CT	EX	PF	PA	OA	TR
CO	0.852						
CT	0.498	0.865					
EX	0.482	0.432	0.862				
PF	0.496	0.477	0.527	0.826			
PA	0.447	0.496	0.483	0.532	0.842		
OA	0.527	0.533	0.503	0.588	0.595	0.819	
TR	0.467	0.517	0.475	0.508	0.482	0.573	0.858

Note: The diagonal values represent the square roots of AVE, and the values below the diagonal indicate the correlations between constructs.

5.5. Model Fit and Multicollinearity Assessment

Model fit and multicollinearity were assessed before testing the structural paths. The standardized root mean square residual is commonly used as a model fit indicator, and values below 0.08 indicate an acceptable model fit (Hu and Bentler, 1999). As shown in **Table 7**, the SRMR value of the estimated model was below the recommended threshold, and the NFI value also indicated an acceptable level of model fit. Multicollinearity was examined using variance inflation factor values. In PLS-SEM, VIF values below 5 generally indicate that multicollinearity is not a serious concern (Sarstedt et al., 2021). As presented in **Table 8**, all VIF values were below the recommended threshold. Therefore, the structural model did not show serious multicollinearity problems.

Table 7. Model Fit Assessment

	Saturated model	Estimated model
SRMR	0.041	0.062
d_ULS	0.737	1.66
d_G	0.334	0.369
Chi-square	817.93	875.785
NFI	0.888	0.88

Table 8. Multicollinearity Assessment

Path	VIF
TR → PF	1.586
TR → PA	1.662
CO → PF	1.562
CO → PA	1.625
EX → PF	1.489
EX → PA	1.611
CT → PF	1.577
CT → PA	1.620
PF → PA	1.716
PF → OA	1.395
PA → OA	1.395

5.6. Structural Model and Hypothesis Testing

The structural model was tested using SmartPLS 4.0, and the results are presented in **Table 9** and **Figure 2**. Among the 11 hypothesized paths, 10 were statistically significant, while only the path from consistency (CO) to perceived authenticity (PA) was not significant. Transparency (TR), consistency (CO), explainability (EX), and controllability (CT) all had significant positive effects on perceived fairness (PF), supporting H1a, H2a, H3a, and H4a. These results indicate that job seekers are more likely to perceive AI interview systems as fair when the systems provide clear information, apply stable evaluation standards, offer understandable explanations, and allow opportunities for feedback or correction. Regarding perceived authenticity (PA), transparency (TR), explainability (EX), and controllability (CT) showed significant positive effects, supporting H1b, H3b, and H4b. However, consistency (CO) did not significantly influence perceived authenticity; therefore, H2b was not supported. This suggests that stable and uniform system operation may contribute to fairness perceptions, but it may not be sufficient for job seekers to perceive the AI interview system as a credible, reasonable, or human-centered recruitment procedure. In addition, perceived fairness (PF) significantly influenced perceived authenticity, and both perceived fairness and perceived authenticity significantly influenced organizational attractiveness (OA). Therefore, H5, H6, and H7 were supported. Overall, these findings show that AI interview system characteristics influence job seekers' evaluations of organizations through their perceptions of fairness and authenticity.

Table 9. Path Analysis Results

Path	Original sample	STD	t-value	p-value	Result
TR → PF	0.210	0.049	4.301	0.000	Supported
TR → PA	0.142	0.054	2.621	0.009	Supported
CO → PF	0.191	0.050	3.801	0.000	Supported

Path	Original sample	STD	t-value	p-value	Result
CO → PA	0.086	0.045	1.902	0.057	Not supported
EX → PF	0.267	0.048	5.595	0.000	Supported
EX → PA	0.165	0.048	3.434	0.001	Supported
CT → PF	0.158	0.047	3.340	0.001	Supported
CT → PA	0.195	0.051	3.863	0.000	Supported
PF → PA	0.238	0.057	4.173	0.000	Supported
PF → OA	0.379	0.054	6.954	0.000	Supported
PA → OA	0.393	0.052	7.577	0.000	Supported

To examine whether respondents' demographic characteristics influenced the major study variables, independent-samples t-tests and one-way ANOVA were conducted. As shown in Table 13, no significant differences were found in organizational attractiveness, perceived fairness, or perceived authenticity across gender, employment status, age, educational level, current job-seeking status, number of AI interview experiences, and AI familiarity (all $p > .05$). These findings suggest that respondents' evaluations of AI interview systems were relatively consistent across demographic groups.

The absence of significant demographic differences suggests that perceptions of AI interview systems may be shaped more by system-related characteristics than by individual demographic backgrounds. Regardless of age, gender, educational attainment, employment status, or AI experience, respondents demonstrated similar evaluations of fairness, authenticity, and organizational attractiveness. This finding supports the argument that applicants' reactions to AI-mediated recruitment are primarily influenced by how the system operates rather than who the applicant is.

Furthermore, the lack of demographic differences provides additional support for the generalizability of the proposed model. Since respondents with different demographic backgrounds exhibited similar perceptions, the effects of AI interview system characteristics may be applicable across diverse applicant groups.

To further examine whether significant differences existed across demographic groups, independent-samples t-tests and one-way analysis of variance (ANOVA) were conducted on organizational attractiveness, perceived fairness, and perceived authenticity. The results are presented in **Table 10**. The findings indicate that no significant differences were observed in organizational attractiveness, perceived fairness, or perceived authenticity across demographic variables, including gender, employment status, age, educational level, current job-seeking status, AI interview experience, and AI familiarity (all $p > .05$). These results suggest that job seekers with different demographic backgrounds generally evaluated AI interview systems in a consistent manner. In other words, perceptions of AI interview systems appear to be influenced more by system-related characteristics than by individual demographic characteristics. Furthermore, these findings provide additional support for the generalizability of the proposed research model. Since respondents from different demographic groups exhibited similar evaluations of the key study variables, the subsequent structural model analysis can more accurately examine the effects of AI

interview system characteristics on perceived fairness, perceived authenticity, and organizational attractiveness.

Table 10. Results of Differences in Key Variables by Demographic Characteristics

Category	Analysis Method	Group Classification	Organizational Attractiveness	Perceived Fairness	Perceived Authenticity	Result
Gender	Independent Samples t-test	Male / Female	$t = .331$, $p = .741$	$t = .684$, $p = .494$	$t = -.432$, $p = .666$	No significant difference
Employment Status	Independent Samples t-test	First-time Employment / Re-employment	$t = -.014$, $p = .989$	$t = -1.108$, $p = .269$	$t = .015$, $p = .988$	No significant difference
Age	One-way ANOVA	≤ 20 / 20s / 30s / 40s / ≥ 50	$F = .688$, $p = .601$	$F = .107$, $p = .980$	$F = .961$, $p = .429$	No significant difference
Highest Education Level	One-way ANOVA	High School or Below / Junior College / University / Master's Degree / Doctoral Degree	$F = 1.661$, $p = .158$	$F = .665$, $p = .617$	$F = .516$, $p = .724$	No significant difference
Current Job-Seeking Status	One-way ANOVA	Student /Preparing for Employment / Employed & Exploring Career Opportunities / Unemployed & Actively Seeking Employment / Other	$F = .437$, $p = .727$	$F = .486$, $p = .692$	$F = .441$, $p = .724$	No significant difference
Number of AI Interview Experiences	One-way ANOVA	1–2 Times / 3–5 Times / 6 Times or More	$F = .165$, $p = .848$	$F = .428$, $p = .652$	$F = .151$, $p = .860$	No significant difference
AI Familiarity	One-way ANOVA	Not Familiar at All / Slightly Familiar / Neutral / Familiar / Very Familiar	$F = 1.517$, $p = .196$	$F = 1.207$, $p = .307$	$F = 1.298$, $p = .270$	No significant difference

Table Note. Independent-samples *t*-tests were conducted for gender and employment status, while one-way ANOVA was conducted for all other demographic characteristics. No statistically significant differences were found in organizational attractiveness, perceived fairness, or perceived authenticity across any respondent characteristics ($p > .05$).

6. Discussion

The findings of this study show that AI interview system characteristics play an important role in shaping job seekers' perceptions of AI-mediated recruitment procedures. Specifically, transparency, consistency, explainability, and controllability all had significant positive effects on perceived fairness. This result supports organizational justice theory, especially the procedural justice perspective, which argues that individuals evaluate the fairness of a selection procedure based on the clarity of information, consistency of standards, understandability of procedures, and opportunities for voice or correction (Leventhal, 1980; Gilliland, 1993; Colquitt, 2001). In AI interview contexts, job seekers often cannot fully observe how the

system collects information, evaluates responses, or generates results. Therefore, visible procedural cues become important bases for judging whether the AI interview system is fair and acceptable. This finding is also consistent with applicant reaction research, which emphasizes that fairness perceptions in selection systems influence applicants' evaluations of recruitment procedures and organizations (Bauer et al., 2001; Hausknecht et al., 2004).

The results also indicate that transparency, explainability, and controllability significantly enhance perceived authenticity. This suggests that job seekers are more likely to perceive an AI interview system as a formal, credible, and reasonable recruitment procedure when the system provides clear information, understandable explanations, and opportunities for feedback or correction. This finding extends previous AI recruitment research by showing that applicants' responses to AI interview systems are not limited to perceived fairness or efficiency, but also include whether the system appears legitimate and aligned with the real purpose of recruitment (Enli, 2015; Vo et al., 2025). It also corresponds with prior studies suggesting that transparency and explainability can reduce uncertainty and strengthen the perceived legitimacy of algorithmic decision-making procedures (Mittelstadt et al., 2019; Martin and Waldman, 2023).

A noteworthy finding is that consistency significantly influenced perceived fairness but did not significantly influence perceived authenticity. This means that applying stable and uniform evaluation standards may help job seekers believe that applicants are treated under the same rules, thereby strengthening fairness perceptions. However, consistency alone may not be sufficient for job seekers to perceive the AI interview system as a genuine, credible, or meaningful recruitment procedure. In other words, standardized operation can signal procedural stability, but it does not necessarily communicate the system's purpose, responsibility, or suitability as a formal recruitment process. Rather than introducing a wholly new construct, this study extends the concept of perceived authenticity by contextualizing it within AI-driven recruitment settings, demonstrating that authenticity perceptions operate distinctly from, and add explanatory value beyond, trust and credibility in algorithmic evaluation.

Finally, perceived fairness had a significant positive effect on perceived authenticity, and both perceived fairness and perceived authenticity significantly enhanced organizational attractiveness. This result supports fairness heuristic theory, which explains that individuals rely on fairness information to judge whether a system or authority is trustworthy and acceptable when they face uncertainty (Lind, 2001; Lind and Van den Bos, 2002). In the AI interview context, when job seekers perceive the interview procedure as fair, they are more likely to regard the system as credible and legitimate. Moreover, the significant effects of perceived fairness and perceived authenticity on organizational attractiveness indicate that AI interview systems are not merely technical tools for recruitment efficiency. Rather, they serve as important contact points through which applicants infer organizational values, credibility, and employer attractiveness. This finding is consistent with recruitment research showing that applicants' experiences during selection procedures can influence their evaluations of organizations as potential employers (Highhouse et al., 2003; Chapman et al., 2005; Luo et al., 2025). Therefore, organizations using AI interview systems should recognize that applicants' perceptions of fairness and authenticity can shape their broader evaluations of the organization.

7. Limitations and Directions for Future Research

This study has several limitations that should be considered when interpreting the findings. First, the data were collected from Chinese job seekers with prior experience in AI interviews. Although this sample is appropriate for examining perceptions of AI interview systems in the Chinese recruitment context, the majority of respondents were under 30 and reported only one to two prior AI interview experiences. This demographic and experiential composition may limit the generalizability of our findings to older job seekers or to populations with greater exposure to algorithmic hiring tools. Future studies could conduct cross-cultural and age-stratified comparisons to examine whether job seekers in different institutional, cultural, age, or labor market environments evaluate AI interview systems in similar ways.

Second, this study used cross-sectional survey data. Therefore, although the findings reveal significant relationships among AI interview system characteristics, perceived fairness, perceived authenticity, and organizational attractiveness, they cannot fully explain how job seekers' perceptions change over time. Future research could adopt longitudinal or experimental designs to examine how applicants' perceptions develop before, during, and after AI interview experiences.

Third, this study focused on four key characteristics of AI interview systems: transparency, consistency, explainability, and controllability. However, applicants' reactions to AI interviews may also be influenced by other factors, such as privacy concerns, AI literacy, technology anxiety, trust in AI, perceived usefulness, and previous experience with digital recruitment tools. Future studies could incorporate these variables to provide a more comprehensive understanding of applicant reactions to AI-mediated recruitment.

Finally, this study examined perceived fairness and perceived authenticity as key psychological perceptions influencing organizational attractiveness. Future research could further investigate additional psychological mechanisms, such as trust, perceived legitimacy, emotional response, and perceived organizational warmth. In addition, future studies may test mediation or moderation effects more explicitly to clarify how AI interview system characteristics shape applicants' attitudes and behavioral intentions.

8. Conclusion

This study explored how the characteristics of AI interview systems affect job seekers' perceptions and their evaluation of organizations. Based on organizational justice theory and fairness heuristic theory, four system characteristics—transparency, consistency, explainability, and controllability—were examined as factors influencing perceived fairness and perceived authenticity. Using survey data collected from Chinese job seekers with prior AI interview experience, this study confirmed that all four characteristics had positive effects on perceived fairness. This indicates that applicants tend to judge the fairness of AI interview systems according to whether the process is clear, consistent, understandable, and open to feedback or correction.

The findings also showed that transparency, explainability, and controllability had positive effects on perceived authenticity, while consistency did not show a significant effect. This result suggests that applying the same standards to all applicants may help improve fairness perceptions, but it does not necessarily make the system appear more genuine, credible, or meaningful as a recruitment procedure. In other words, job seekers may need more than standardized operation to perceive

an AI interview system as an authentic part of the hiring process. Clear information, understandable explanations, and opportunities for feedback appear to be more closely related to such perceptions.

In addition, perceived fairness was found to increase perceived authenticity, and both perceived fairness and perceived authenticity positively influenced organizational attractiveness. These results suggest that AI interview systems are not merely technical tools used to improve recruitment efficiency. Rather, they function as important points of contact between applicants and organizations. The way an AI interview system is designed and operated can influence how applicants interpret the organization's values, credibility, and attractiveness as a potential employer.

This study contributes to the literature on AI-based recruitment by focusing specifically on AI interview systems and by introducing perceived authenticity as an important psychological perception in applicants' evaluations. The findings also provide practical implications for organizations using AI interviews. Companies should not rely only on efficiency and standardization when designing such systems. They should provide clear guidance on evaluation criteria, offer understandable explanations of assessment results, and create channels through which applicants can give feedback or request correction. Such efforts may help organizations build AI interview systems that are not only efficient, but also fair, credible, and more acceptable to job seekers.

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