Can Candidates Perform Better? Examining the Effects of Training on Performance in AI-Based Interviews

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Abstract. While AI interviews provide considerable convenience for employers in selecting candidates, studies have shown that AI interviews also face challenges such as poor candidate performance and resulting validity concerns. Therefore, previous research has suggested offering training to candidates to alleviate these concerns. However, given the inherent differences in evaluation mechanisms between AI and traditional interviews, little is known about whether training can improve candidates' performance in AI interviews and the underlying mechanisms involved. This study recruited 120 undergraduate students, randomly assigned them to training and no-training groups, and conducted a between-subjects simulated interview experiment, aiming to examine how AI interview training affects interview performance, the underlying mediating mechanisms, and relevant boundary conditions. Results showed a positive relationship between AI interview training and interview performance. Mediation analysis revealed that trained participants reported higher self-efficacy of human-AI interaction, which in turn led to better AI interview performance. Moderation analysis showed that the effect of AI interview training on self-efficacy of human-AI interaction was stronger for participants with higher levels of AI resistance.

Keywords: AI Interview, Training, AI Interview Performance.

1 Introduction

Artificial Intelligence (AI) is becoming a a key area of interest for employers and is increasingly applied in interviews. AI interview is defined as "any application of artificial intelligence used by employers in the recruitment and selection of job candidates", with AI technology being applied in the outreach, screening, assessment, and facilitation stages of recruitment[1]. Compared to traditional selection methods, preliminary research has highlighted the advantages of AI interviews in talent selection, such as increased interview efficiency, more accurate identification of candidate-job fit[2], and less prejudice[3]. The benefits brought by AI technology have made recruiters increasingly see AI as a liberator that frees them from the intensive labor of recruitment[4]. In fact, recent statistics show that approximately 79% organizations reported using AI

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exclusively for recruitment in 2022[5]. And it is expected that by 2025, this proportion will increase to 87%, where 79% of recruiters believe that AI will soon be capable of making hiring decisions[6]. Therefore, AI recruiting is increasingly considered a valuable asset in today's "war for talent".

However, due to the profound and substantial impact that recruitment decisions have on both applicants and employers, AI interviews also face notable challenges. On one hand, job seekers often hold negative and insufficiently informed perceptions of AI interview[7], leading to inferior performance in technology-mediated interviews compared to traditional face-to-face formats[8]. On the other hand, inaccurate candidate performance poses a concern for employers, as it undermines employers' ability to effectively identify truly valuable talent.

Providing candidates with training about interview tools is considered an effective way to alleviate related concerns, as informing applicants about key considerations or explaining the rationale behind specific selection methods before the interview can enhance candidate reactions and performance[9]. Maurer et al. found that training candidates on selection tools (e.g., structured interviews) improved their interview scores, and showed that trained applicants exhibited greater predictive validity and reliability than those without training[10]. Furthermore, in the context of technology-mediated asynchronous video interviews (AVIs), Roulin and Bourdage also provided evidence that training enhances candidate performance[11]. Although the effectiveness of training has been established, little is known about whether training can effectively improve candidate performance in AI interviews. First, AI interviews pose challenges to the effectiveness of traditional training. In AI interviews, the evaluator of candidate performance has shifted from human interviewers to AI systems[12], marking a foundational change in the domain of interview training research. Second, research on AI interviews is still in its early stages, with most studies focusing on comparing how AI algorithms versus human recruiters affect applicant reactions[13], while paying little attention to interventions aimed at improving candidate performance in AI interviews.

This study aims to examine the impact of AI interview training on candidates' AI interview performance and to identify the underlying explanatory mechanisms and boundary conditions. Drawing on Bandura's social learning theory[14], we propose that training enhances candidates' AI interview performance by increasing their self-efficacy of human-AI interaction. Furthermore, we suggest that candidates' AI resistance serves as a key boundary condition moderating the relationship between AI interview training and self-efficacy of human-AI interaction in AI interviews. Our findings offer both theoretical and practical guidance for employers using AI interviews to provide candidate training. In particular, for candidates with high levels of AI resistance, training can help them better demonstrate their true abilities, thereby assisting employers in selecting qualified candidates. Additionally, it may foster more positive perceptions of AI interview, which may indirectly influence the employers' reputation, image, and brand[15]. Furthermore, this study expands upon prior literature on traditional interview training[16], by validating the effectiveness of training in the emerging context of AI interviews and offering a theoretical foundation for future research.

2 Theory and Hypothesis

The concept of self-efficacy from Bandura's social learning theory[10] provides a useful framework for understanding the impact of AI interview training on AI interview performance and the potential mediating mechanisms. Self-efficacy is defined as an individual's belief in their ability to successfully complete specific tasks[18]. In the context of AI interviews, we extend the notion of self-efficacy to self-efficacy of human-AI interaction, which refers to individuals' perceived ability to interact effectively with AI during the interview. Research on self-efficacy has shown that training interventions focusing on knowledge building, skill acquisition, and performance feedback can enhance candidates' self-efficacy[19], thereby improving interview motivation and performance. Therefore, when AI interview training helps candidates gain a comprehensive understanding of AI interviews and provides essential skills and feedback, they are more likely to perceive themselves as capable of interacting effectively with AI interviewers, leading to better interview performance. Additionally, such training appears especially beneficial in increasing self-efficacy of human-AI interaction in candidates who are initially resistant to AI. Candidates with high levels of AI resistance may feel anxious or uneasy in AI interviews, which can diminish their sense of self-efficacy. However, by providing information on evaluation mechanisms and related aspects, AI interview training can reduce these negative emotions, thereby enhancing its effectiveness in fostering self-efficacy of human-AI interaction. Accordingly, the following hypothesis is proposed:

H1: AI interview training positively influences candidates' self-efficacy of human-AI interaction.

H2: AI interview training positively influences candidates' AI interview performance

H3: Self-efficacy of human-AI interaction plays a mediating role in the relationship between AI interview training and AI interview performance.

H4: AI resistance positively moderates the relationship between AI interview training and self-efficacy of human-AI interaction.

3 AI Interview Training

The AI interview training comprised two key components: a training manual and corresponding face-to-face instruction. The specific content is presented in Table 1.

Table 1. Description of training content.

No.	Training content	Type	Description	Method	Time
1	AI interview introduction	Core	The Definition and development of AI interviews. AI interview versus traditional interview. Strengths/weaknesses of AI interviews.	Instruction	5
2	Assessment principles and dimensions	Core	Assessment Principles (Structured Behavior Event Interview). Assessment characteristics and six key competencies of AI interview assessment.	Instruction	5

3	Sample questions	Core	Common AI interview question types, real question answer cases, and answer strategies.	Instruction Modeling	10
4	Peripheral techniques	Peripheral	Speech volume or loudness, fluency. Eye contact, smiling, facial cues, body language.	Instruction Modeling	5
5	Interview narrative skill	Core	Discussion of STAR technique. Participants work through first two characteristics (achievement and conscientiousness) and instructed to work through others on own.	Modeling Practice	10
6	AI interview observation	Core	Participants watch the complete AI interview process and share their experiences with job seekers who have participated in AI interviews.	Practice Feedback	5
7	Simulated AI interviews	Core	Participants use the AI interview trial account we provide to experience the interview and receive feedback on the results.	Practice Feedback	5

3.1 Training Manual

The development of the AI interview training manual was informed by the work of Tross and Maurer[16], and the training content was divided into two categories: peripheral information (tactics that are peripheral or less central to core job requirements) and core information (knowledge that focuses on job-relevant information and reduces irrelevant sources of variance). Specifically, the peripheral information included verbal cues (i.e., speech volume), nonverbal cues (i.e., smiling), and impression management tactics. The core information covered the AI interview introduction, assessment principles and dimensions, sample questions, the narrative rules of the STAR method (Situation, Task, Action, and Result), AI interview observation and simulated AI interviews.

3.2 Training Methods

Our training methods were inspired by Macan's Behavioral Skills Training (BST) framework[17]. BST involves the use of instructions and modeling of target behaviors, followed by opportunities for practice and feedback. In the training on peripheral information, we first provided instructions and modeled the relevant skills. For the core information training, we used instructional methods for the AI interview introduction and the assessment principles and dimensions. The sample questions section employed both instructional and modeling techniques. For the narrative rules of the STAR method, we primarily used modeling and practice-based techniques. The AI interview observation and simulated AI interview segments involved practice and feedback methods.

4 Methods

4.1 Sample

136 undergraduate students participated in the study for course credit. Participants were excluded for two reasons: (1) duplicate participation (e.g., the same individual com-

pleting the study multiple times using different AI interview accounts); and (2) extremely incomplete or unusable interview responses (e.g., missing video or audio). The final valid sample consisted of 120 participants. Among the participants, 63.3% were female; 96.7% of participants were between 18 and 22 years old; 98.3% of the participants had no prior experience with AI interviews; 67.5% of participants indicated that they had heard of AI interviews but were not familiar with them.

4.2 Procedure and Design

To simulate a realistic job application environment and enhance participants' motivation to engage in the AI interview, participants completed an AI interview for an actual job posting, with top performers awarded an additional internship opportunity. A basic randomization procedure was employed to randomly assign participants to one of two between-subjects conditions (AI interview training vs. no AI interview training). More specifically, each participant was assigned a unique number and randomly allocated to a group using a random number generator. This procedure was conducted by an independent researcher who was not involved in the intervention or outcome evaluation to ensure the concealment of allocation and reduce potential bias.

Participants in the training group received a 45-minute face-to-face training session and were given the AI interview training manual; no intervention was provided to the control group. All participants reviewed a job description for a management trainee position, received basic instructions on using the AI interview platform, and then completed an AI interview consisting of five structured behavioral questions. After the interview, all participants completed questionnaires measuring self-efficacy of human-AI interaction, AI resistance and demographic information.

4.3 Measures

Self-efficacy of Human-AI Interaction. We adopted six items from Pütten and Bock's study on self-efficacy of human-AI interaction[20]. We slightly reworded the items to capture participants' experience interacting with AI specifically, rather than generic robots (e.g., replacing "I would feel comfortable while interacting with the robot" with "I would feel comfortable while interacting with the AI recruiter"). Responses were recorded on a 5-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). The Cronbach's alpha coefficient for this scale was 0.857.

AI Resistance. We adopted four items from Jussupow et al.'s study on AI resistance[21]. These items were also slightly reworded to reflect interview-specific contexts (e.g., "I do not want Sherlock to change the way I interact with other people on my job" was modified to "I don't want AI to change the way I interact with recruiters during interviews"). Responses were recorded on a 5-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). The Cronbach's alpha coefficient for this scale was 0.878.

AI Interview Performance. AI interview performance was measured using the L4-level score provided by the AI interview platform. The AI interview system generates the L4-level score based on video analysis, voice analysis, semantic understanding, facial feature recognition, and other measurement technologies. The AI interview performance score ranges from 1 to 5.

4.4 Results

Main Effects. Table 2 presents the descriptive statistics and correlation analysis results for the variables in this study. One-way ANOVAs were conducted to test Hypotheses 1 and 2, with AI interview training as the independent variable and self-efficacy of human-AI interaction and AI interview performance as dependent variables. Table 3 reports the results of follow-up analyses for between-subject effects, along with the means and standard deviations for each condition.

Table 2. Descriptive statistics and correlations between main variables.

	M	SD	1	2	3	4	5	6	7	8	9
1	-	-									
2	0.630	0.484	0.047	1							
3	1.030	0.180	-0.096	-0.148	1						
4	1.030	0.180	-0.003	0.045	.483**	1					
5	1.020	0.129	0.128	-0.171	-0.024	-0.024	1				
6	2.020	0.635	0.105	-0.117	-0.005	-0.005	.202*	1			
7	3.379	0.761	0.003	0.016	0.091	0.106	0.021	0.161	1		
8	3.229	0.668	.301**	-0.006	0.029	-0.041	0.004	0.156	0.171	1	
9	2.500	0.565	.193*	.215*	0.082	0.000	0.000	0.141	0.078	.265**	1

Notes: N=120, *p < .05, **p < .01, ***p < .001. 1: Train, 2: Gender, 3: Age, 4: Education, 5: AI Interview Experience, 6: AI Interview Familiarity, 7: AI Resistance, 8: Self-Efficacy in Human-AI Interaction, 9: AI Interview Performance

Consistent with Hypothesis 1, participants who received AI interview training (M = 2.61, SD = 0.52) achieved higher AI interview performance than those without training (M = 2.39, SD = 0.59), $F(1,118) = 4.543$, $p < 0.05$. Consistent with Hypothesis 2, participants who received AI interview training (M = 3.43, SD = 0.63) reported higher self-efficacy of human-AI interaction than those who did not receive training (M = 3.03, SD = 0.65), $F(1,118) = 11.78$, $p < 0.001$.

Table 3. Effect of AI interview training on interview outcomes.

	No Training		Training		One-way ANOVAs	
	M	SD	M	SD	F	partial η^2
Self-efficacy in human-AI interaction	3.03	0.65	3.43	0.63	11.78***	0.09
AI interview performance	2.39	0.59	2.61	0.52	4.543*	0.04
N	59		61			

Note: N = 120, *p < .05, **p < .01, ***p < .001

Mediation Analyses. With SPSS 27, we used Model 4 of the PROCESS to test the mediating effect[22]. The results are presented in Fig. 1 (N = 120; reported values include unstandardized estimates with standard errors on top line and standardized Betas at bottom line). Consistent with Hypothesis 3, the effect of training on AI interview performance was fully mediated by self-efficacy of human-AI interaction. Specifically, we found a significant path from AI interview training to self-efficacy of human-AI interaction (β = 0.60), and from self-efficacy of human-AI interaction to AI interview performance (β = 0.23). In addition, the indirect effect of AI interview training on AI interview performance through self-efficacy of human-AI interaction was statistically significant (indirect effect = 0.08, SE = 0.05, 95% CI [0.02, 0.32]). These results suggest that individuals who received training had higher levels of self-efficacy in interacting with AI during AI interviews, which in turn led to improved interview performance.

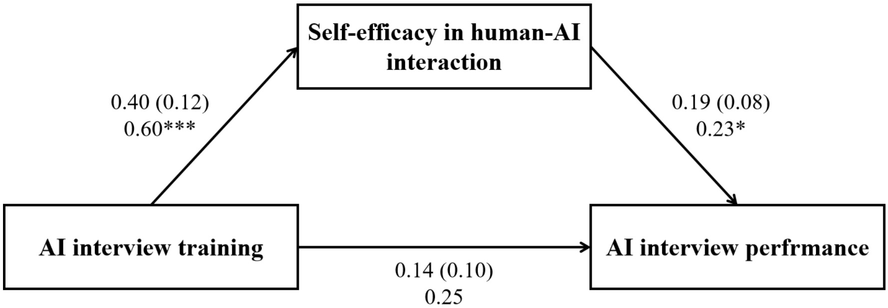

Fig. 1. Mediation Model.

Moderation Analyses. Hierarchical regression analysis was used to examine the moderating effect of AI resistance. The results are displayed in Table 4. Consistent with Hypothesis 4, there was a significant interaction between AI resistance and AI interview training ($b = 0.12$, $p < 0.05$). This positive moderation effect is illustrated in Fig. 2. As shown, individuals with high AI resistance (simple slope = 0.60, $p < 0.05$) exhibited a steeper slope compared to those with low resistance (simple slope = 0.28, $p < 0.001$). These findings indicate that the positive effect of AI interview training on self-efficacy of human-AI interaction is more significant among individuals with higher AI resistance.

Table 4. Regression Results.

	Self-efficacy in human-AI interaction		AI interview performance
	M1	M2	M3
C	2.523*** (0.270)	2.460*** (0.268)	1.702*** (0.306)
AI interview training	0.400*** (0.115)	0.400*** (0.114)	0.131 (0.104)
AI resistance	0.149 (0.076)	0.147* (0.076)	0.012 (0.076)
AI interview training * AI resistance		0.121* (0.058)	-0.091 (0.051)
Self-efficacy in human-AI interaction			0.214** (0.081)
R^2	0.120	0.152	0.110
ΔR^2	0.120	0.032	0.110
F	7.941***	6.926***	0.009**

Note: N = 120, *p < .05, **p < .01, ***p < .001

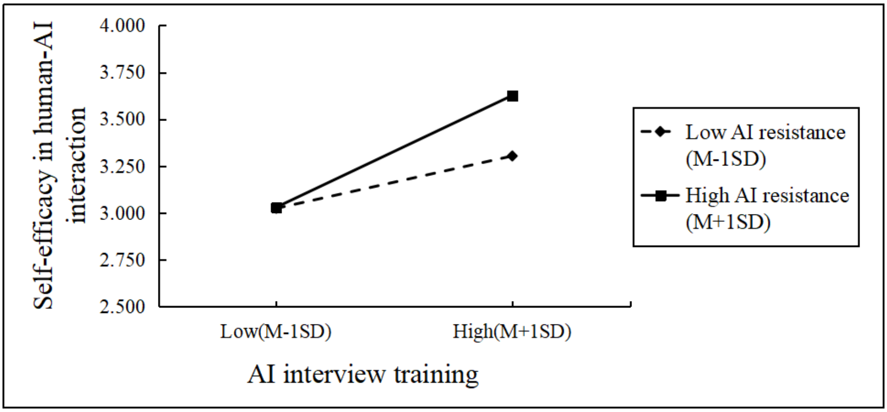

Fig. 2. Moderating effect.

4.5 Discussion

The research findings offer practical implications for employers. First, our findings indicate that training can enhance candidates' performance in AI interviews by increasing their self-efficacy in human-AI interaction. Notably, the training was designed to help candidates focus on job-relevant information sought by the interview and to help them understand and accurately convey such information, rather than to improve any job-related competencies of the candidates themselves[16]. This interpretation is supported by our mediation analysis. Therefore, under our training framework, improved candidate performance in AI interviews reflects enhanced interview validity and measurement accuracy. This provides empirical support for the effectiveness of the training. Accordingly, employers can adopt our training framework to improve AI interview effectiveness without raising fairness concerns. Second, our moderation analysis offers additional support for providing AI interview training. Resistance to AI implementation is inevitable among some individuals, but our results suggest that training can alleviate such resistance. Therefore, for employers eager to adopt AI interviews and advocate for their effectiveness, preparing AI interview training for potential candidates is essential.

Although our analysis has shown preliminary evidence to support our theoretical model, our experiment only included 120 participants due to periodic difficulties in data collection.We suggest that future research can expand the sample size and not limit the sample selection to undergraduate students, but instead seek out real job seekers. We believe that this can better validate the general effect of AI interview training on AI interview performance.

5 Conclusion

Drawing on Bandura's social learning theory[14], our findings provide initial empirical support for the idea that AI interview training enhances candidates' self-efficacy in human-AI interaction, thereby leading to improved AI interview performance. In addition, we found that AI resistance positively moderated the relationship between AI interview training and self-efficacy in human-AI interaction. In other words, AI interview training is particularly beneficial for candidates who exhibit high AI resistance. Compared to those with low resistance, candidates with higher levels of AI resistance showed greater improvements in self-efficacy in human-AI interaction, which in turn translated into stronger AI interview performance. This study offers practical insights for the implementing of AI interview training and lays a theoretical foundation for future research in this area.

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