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Empirical research on the application of AI mock interviews in enhancing graduate perceived employability: a case study in Hangzhou, China

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Abstract

Employability has been a key area of interest for researchers, especially as China faces increasing pressure in the labor market due to shifting supply and demand dynamics. Despite a steady increase in the number of graduates over the past five years, employment rates have declined, and the rates of slow employment, a slower state of employment, which usually manifests itself in graduates failing to find a job for a long time after graduation or choosing to delay employment, have been rising. Graduates' self-confidence in their employability is one of the most critical indicators of successful employment. Given the rapid digitization in higher education and employment preparation, artificial intelligence (AI) technologies, such as AI mock interviews, have gained increasing attention. Previous researches have shown that innovations, such as digitalization, asynchronous methods, and AI mock interviews, are beneficial for career preparation. However, empirical studies on the application of AI mock interviews in China remains limited. This study aims to investigate the impact of AI mock interviews in improving graduate perceived employability and short-term employability performance through a quasi-experimental design. A total of 42 participants were selected via convenience sampling for the experiment conducted in Hangzhou, Zhejiang, China. The findings suggest that AI mock interviews can improve graduate perceived employability and its dimensions except reconsideration of commitment, and also effectively optimize graduates' employability performance in real interview scenarios. This research provides new insights for higher education institutions focusing on improving career planning strategies and offers a practical foundation for enhancing graduates' self-assessment of their perceived employability in a more competitive labor market.

Keywords AI mock interviews · Graduate perceived employability · Perceived program relevance · Program and self-awareness of program · Career commitment · Career exploration and awareness

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1 Introduction

Employability has long been a crucial area of focus in educational and labor market research due to its significant impact on the success of graduates in the labor market. With the rise of Industry 4.0, driven by automation and artificial intelligence (AI), the job market's demands for graduate employability have shifted beyond just professional knowledge and soft skills to include elements such as intrinsic value and market value capital (Donald et al., 2017). In response, researchers have increasingly advocated the integration of AI technologies in career preparation, particularly through AI-driven mock interviews (Gomes & Santos, 2023; Kothari et al., 2024; Lewton & Haddad, 2024). For example, AI-powered mock interview technology is being incorporated into the career preparation process in higher education to assist graduates in better engaging with self-discovery and career exploration. As Trait-Factor Theory (1909) by Parsons suggests, a key condition for person-vocation fit is that individuals must understand both themselves and the world of work (Xu, 2022). Therefore, AI mock interviews have become a popular and effective method for preparing graduates to navigate the complexities of a competitive labor market.

Jacqueline Lewton (2024) conducted a study involving 234 pharmacy students to explore whether AI-based mock interview software would impact their confidence and interview preparation. The results showed that 79.9% of the students recognized the effectiveness of the AI mock interviews. Additionally, 34.5% and 38.9% of the students reported feeling highly or moderately confident in their abilities to secure a second interview or job opportunity (Lewton & Haddad, 2024). LeAnn Wilkie & Joseph Rosendale (2024) conducted a study on students' satisfaction and perceptions of virtual mock interviews during the COVID-19 pandemic. The survey revealed that students had a positive experience, as they believed these virtual interviews helped enhance their ability to perform better in real interviews (Wilkie & Rosendale, 2024). Kim (2023) invited three job-seeking university students to experience the AI mock interviews and collected their feedback. They indicated that the AI mock interviews could alleviate their anxiety and fear, and suggested the need for further experiential education on the AI mock interviews and the provision of specific feedback in practical training (Kim, 2023). However, despite these encouraging developments, there is a lack of literature on experimental interventions to explore the positive impact of advanced generative AI techniques (e.g., mock interviews) integrating graduate career readiness learning on graduate perceived employability (Almassaad et al., 2024; Lund & Wang, 2023), especially in the specific context of the labor market in Hangzhou, China. There is also a lack of in-depth research on the impact of AI mock interviews on key dimensions of perceived employability. In this context, this study addresses the gaps identified in previous literature through an experimental intervention.

The purpose of this study is to examine the impact of AI mock interviews on graduates' perceived employability through a quasi-experimental design. The rationale for this study lies in the limitations of traditional interview preparation methods, which often lack dynamic, personalized, and real-time feedback. Because GenAI technology is best suited to augment traditional career readiness learning methods by enhancing interactivity and personalizing the learning experience (Alier et al., 2024).

Traditional approaches, such as case studies, observations, and peer role-playing, are useful but fall short in preparing students for real-world interactions. Case studies encourage critical thinking but do not allow students to practice skills directly with clients or hiring managers. Similarly, observations, while valuable for analyzing good and poor practices, provide no opportunities for hands-on experience. Role-playing offers more practical experience, but performing in front of peers and instructors can induce anxiety (Baker & Jenney, 2022; Mackey & Sheingold, 1990). To address these challenges, this study utilizes an AI mock interview system, allowing users to engage in realistic simulations, receive immediate feedback on both verbal and non-verbal communication, and refine their job-seeking strategies. The system adapts to individual career goals and skill levels, offering personalized recommendations for improvement. By focusing on individual mock interviews, this study examines how AI-driven tools can enhance graduates' self-confidence in employment and optimize career readiness in the face of employment pressures. Thus, the study is guided by three research questions:

1. Does AI mock interviews significantly enhance graduate perceived employability?
2. Does graduate perceived employability increase with the frequent use of AI mock interviews?
3. Does AI mock interviews have a positive impact on graduates' employment performance?

2 Literature review

2.1 Career construction theory (CCT)

The Career Construction Theory, proposed by Savickas (2002), is grounded in the ideological foundations of personal constructivism, social constructivism, and post-modernism (Savickas, 2005). The theory believes that the core of career development lies in an individual's ability to create a dynamic and continuous process of adaptation through the ongoing adjustment and construction of the interaction between the self and the external world, and each person crafts their own unique career story along the way (Wang & Li, 2024). CCT emphasizes how individuals actively shape their career identities and understand the evolving trajectories of their career development through self-narratives and the construction of meaning, and it comprises three components, namely, professional personality, career adaptability and life themes (Savickas & Porfeli, 2012). According to Savickas and Porfeli (2012), achieving stable adaptation at all stages of career development requires considering not only an individual's adaptive readiness, resources, responses, and outcomes, but also the influence of situational factors on these components (Savickas & Porfeli, 2012). That is, as the external environment continues to evolve, an individual's ability to effectively adapt and adjust in a complex professional world becomes crucial to their career success.

Vocational personality refers to an individual's career-related abilities, needs, values, and interests, and it focuses on the aspects an individual requires when constructing a career. Career adaptability refers to the resources individuals possess to manage career development tasks, transitions, and challenges, and it emphasizes the process of constructing careers. The life theme, as a dynamic system, focuses on explaining why individuals make specific career choices and the meaning behind those choices. It highlights the uniqueness of the individual in a given context and offers a perspective through which the individual perceives the world (Wang & Li, 2024).

Specifically, objective personality traits are crucial factors of adaptive readiness that contribute to an individual's career construction and are even more fundamental to CCT (Chen & Zhang, 2024). This aligns with the findings of several previous studies, which suggest that individuals with intrinsic motivation to actively seek breakthroughs are better able to engage deeply in the career-building process (Cai et al., 2015; Jiang et al., 2019). These individuals are more likely to explore career options and show greater resilience when confronted with the complexity and variability of the occupational world, thereby fostering richer perspectives on career development (Gao & Qiao, 2022). In addition, another key element of CCT is career adaptability (Savickas, 2005). For graduates, career adaptability and skill preparation are essential for successful job search. Previous studies have shown that AI mock interview technology helps graduates enhance self-awareness and adapt themselves more effectively to meet workplace challenges, aligning with the concept of career adaptability in CCT (Kim, 2023; Lewton & Haddad, 2024; Wilkie & Rosendale, 2024). However, how to effectively utilize the benefits of AI technology to enhance graduate perceived employability and alleviate employment anxiety within the framework of CCT has emerged as a new research perspective on the integration of AI in higher education in the context of Industry 4.0.

The most crucial step in Career Construction Theory, in the process of self-awareness and career exploration, is the individual's reflection on and reconstruction of roles to address career challenges (Savickas, 2012). Through repeated mock interviews, graduates can identify deficiencies in areas such as expression, emotional control, and problem-solving, which helps enhance their self-awareness and strengthen their career identity. This aligns with the view by Dawn Bennett (2021) that the perception of employability is ultimately shaped within the framework of graduates' metacognition (Bennett & Ananthram, 2021). Career construction theory can be understood as the concept that everyone is like a 'career scientist', actively shaping their personalized career by enhancing their psychological capital through metacognitive skills such as critical thinking, problem-solving, and self-reflection (Römgens et al., 2019).

2.2 Graduate perceived employability (GPE)

Employability differs from employment in that employment is merely a short-term realization of employability (Potts, 2021). Employment refers to securing and maintaining a job, while employability is the ability to acquire and retain a fulfilling job, encompassing personal attributes, transferable skills, and career planning abilities (Hillage & Pollard, 1998). Higher employability enhances candidates' attractiveness in job competitions, leading to short-term employment opportunities while simultaneously boosting long-term employability (Potts, 2021). Erik Berntson et al. (2007)

further break down employability into three stages: career preparation before entering the labor market, maintaining employment, and seeking new opportunities (Berntson & Marklund, 2007). Since the subjects of this experiment are recent graduates, this study focuses on the first stage, where graduates evaluate their positioning in the labor market and their ability to secure a job as they transition from education to employment.

According to Bandura's Social Cognitive Theory, employability is influenced by the interaction of personal, environmental, and behavioral factors (Bandura, 1986). Thus, from a subjective perspective, employability refers to an individual's perception of their ability to secure sustainable employment that aligns with their qualifications (Rothwell et al., 2008). As Forrier and Sels (2003) put it, it is how individuals perceive their career prospects (Forrier & Sels, 2003). Employability has long been considered a complex concept, encompassing dimensions such as occupational identity, self-management, social connectedness, and work-life experience, while perceived employability is only one of the dimensions of employability (Bennett, 2018; Clarke, 2017). For graduates, graduate perceived employability refers to graduates' views and beliefs about their likelihood of successfully obtaining a full-time job after graduation (Rothwell & Arnold, 2007). Some scholars have conceptualized perceived employability as graduates' beliefs about their likelihood of success in the labor market (Ho et al., 2022; Pitan & Muller, 2019).

Prior literature demonstrates that perceived employability is closely linked to how confident graduates feel about their ability to adapt to unstable work environments and capitalize on emerging job opportunities (Jackson & Tomlinson, 2020). Graduates with higher perceived employability are generally more confident in securing new opportunities, which is particularly important in the fast-paced and competitive industries influenced by AI and digitalization. In addition, It is well recognised that higher education institutions play a pivotal role in developing talents capable of making positive contributions in a rapidly changing environment (Denman & Welch, 1997, April; Harvey, 2001; Hoeckel, 2014; Jackson, 2013; Kinash et al., 2016). Consequently, many scholars have called for higher education institutions to enhance the employability of their graduates by adopting teaching and learning strategies that align with the needs of the labor market (Holmes, 2013; Jackson & Tomlinson, 2020). For example, career preparation should be integrated into the curriculum to better equip graduates with the skills and knowledge needed in today's competitive job market (Jackson & Bridgstock, 2019). However, despite the increasing demand for career support, graduates continue to experience uncertainty and anxiety about their employment prospects due to factors like economic instability and evolving industry requirements. Therefore, universities must not only provide career-oriented education but also create a supportive environment that helps graduates rebuild their confidence in navigating the labor market and securing employment.

2.3 AI mock interviews

With the release of ChatGPT-4 and other advanced generative AI technologies, higher education institutions face both new challenges and opportunities in enhancing graduates' career readiness and employability training. AI mock interviews, as an innovative tool, have brought a boon to higher education institutions and graduates in optimizing employment outcomes, because the mock interview process helps bachelor's students to practice virtual interviews in order to improve their confidence (Uppalapati et al., 2025). Powered by advanced algorithms and Natural Language Processing (NLP) models, such as GPT-4, and utilizing deep learning techniques, such as Generative Adversarial Networks (GANs), these latest AI mock interviews have great potential to enhance job search readiness by overcoming the limitations of traditional interview counseling methods (Chen et al., 2024; Koutsoumpis et al., 2024). And artificial intelligence (AI) offers several advantages to society, including tangibility, immediacy, and transparency, enabling faster decision-making, enhanced efficiency, and greater clarity in various processes (Suen & Hung, 2023).

Unlike conventional methods, AI mock interviews can analyze, interpret, and generate interview questions and responses that mimics human interaction, providing participants coherent and contextually appropriate feedback during practice sessions (Qin et al., 2023). Traditional mock interviews were often limited by predefined questions and static scenarios. The optimization of data augmentation techniques not only simulates interviewer feedback more realistically but also continues to narrow the gap between simulated and real interview scenarios (Chen et al., 2024). Specifically, the AI mock interviews can customize interview scenarios based on position and industry, offering graduates a tailored, real-life practice environment while generating dynamic, role-specific questions for real-time dialogue simulation, thus providing a more realistic interview experience (Lewton & Haddad, 2024). Furthermore, AI mock interviews act as virtual interviewers, enabling candidates to receive instant feedback on their responses and to refine their interview techniques in a low-pressure environment (Suen & Hung, 2023). Based on these, these tools adapt to each individual's career aspirations and skill levels, providing targeted feedback on critical elements, such as communication skills, body language, and professionalism (Liaw et al., 2023), while timely feedback is vital in helping students to enhance their overall personalities for learning, confidence, communication and problem solving (Uppalapati et al., 2025). This process of enhanced self-awareness aligns perfectly with the concept of career fit in career construction theory.

AI mock interview platforms like ChatGPT, Big Interview, Pramp, and Interviewing.io offer flexible, accessible solutions that cater to individual preferences. This study selected several highly-rated platforms, giving participants the flexibility to choose the system that best suited their career goals and preferences. The latest mock interview tools utilizing generative AI technology not only can ask the standard questions during interviews but also spontaneous follow-up questions that reflect real-life interview dynamics. This level of interactivity helps graduates build confidence and develop skills that are directly applicable to real-world job interviews. AI-powered mock interview platforms have been increasingly integrated into higher education as part of career preparation programs in the context of accelerating the building of a "digital China" (Shi, 2023), emphasizing how quickly educational institutions are adopting digital tools in modern education and the key role of technology in education (Uppalapati et al., 2025). For example, Renmin University of China has developed a Smart Career Development Center platform, which offers students pre-interview simulations, intelligent resume assessments, and personalized feedback aimed at enhancing employability. This platform helps students practice repeatedly in a low-pressure environment, allowing them to gradually improve their communication, problem-solving skills, and other related capabilities.

Currently, the latest AI mock interviews developed in China have introduced features that automatically identify keywords and generate follow-up questions. This enhances the effectiveness, relevance, richness, and specificity of the simulated interview content, demonstrating a higher level of cognitive skill in artificial intelligence (Kiesel et al., 2024; Meng et al., 2024). This ability to simulate realistic interview environments allows graduates to repeatedly practice while receiving evaluative feedback on their overall performance, which enhances their self-awareness and confident in job-seeking (Lewton & Haddad, 2024). As Pompedda et al. (2020) demonstrated, repeated feedback from mock interviews helps improve the quality of candidate performance (Pompedda et al., 2020). Despite the promising potential of AI mock interviews, as Li et al. (2023) noted, the use of AI in employability remains an evolving field that requires more empirical studies to fully understand its impact on job preparation for graduates (Li et al., 2023).

2.4 AI mock interviews and graduate perceived employability

According to Clarke (2017) and Jackson (2014), graduate employability is constructed through a combination of social factors, including not only individual knowledge and skills but also social capital, such as social class and networks, as well as labor market dynamics (Clarke, 2017; Jackson, 2014). Within the framework of CCT, education is a socialization process that not only imparts knowledge and skills but also helps graduates shape their career paths and enhance their self-awareness of perceived employability by assigning them specific social roles and identities (Chen & Zhang, 2024; Jackson, 2014). In this context, AI mock interviews can be seen as a tool for promoting graduate socialization, allowing graduates to practice and demonstrate their skills and behavioral patterns in a virtual social interaction environment. This, in turn, helps them develop and shape their career perceptions of what it means to be a 'successful jobseeker' within a social interaction context. In addition, graduate employability is not solely the result of individual effort, but it is also shaped by the social demand and expectations of the labor force, and graduates' self-awareness of perceived employability is influenced by their understanding of the labor market (Jackson & Tomlinson, 2020). AI mock interviews help graduates adapt to these social expectations, thereby enhancing their "social acceptance" and competitiveness in the labor market.

Moreover, in the current globalized job market, industries such as artificial intelligence (AI), big data, and online marketing present unique challenges for graduates. Graduates' confidence in employability is linked to various aspects of their learning and career thinking, as employability has been defined by many scholars as "an integral part of the lifelong learning process, continuously evolving throughout one's career to ensure career sustainability" (Donald et al., 2017; Healy et al., 2020). Perceived employability is seen as just one dimension of employability (Bennett, 2018; Clarke, 2017). This study analyzed the impact of AI mock interview technology on graduates' self-awareness of perceived employability. Previous research has shown that perceived employability is positively correlated with confidence and career self-efficacy (Donald et al., 2018). Meanwhile, positive self-perceptions of employability can influence actual employability when entering the labor market and effectively support graduates' career development (Cortellazzo et al., 2020). In addition, career interventions, such as AI mock interviews, can enhance graduates' career maturity, career decision-making certainty, career identity, and self-efficacy in career decision-making (Ho et al., 2022). This also highlights the importance of career readiness learning provided by higher education institutions. Based on this, the researchers concluded that AI mock interviews can enhance graduates' perceived employability and improve their job performance, thereby boosting their chances of employment.

Previous literature indicates that graduates' employability is influenced by various factors. Clarke (2017) suggests that graduates' employability is determined by a combination of human capital, including specific occupational knowledge and transferable higher-order skills such as problem-solving and teamwork, and social capital, such as social class, network embeddedness, and the type and classification of degrees obtained, as well as personal behaviors like career self-management. Additionally, personal traits, such as adaptability and flexibility, and labor market variables, including macroeconomic conditions and the geographic concentration of job opportunities also play significant roles (Clarke, 2017). In this context, graduates are viewed as educational consumers, where skills, competencies, and knowledge become valuable commodities aimed at enhancing their employability in a knowledge-based economy (Jackson, 2014). Therefore, the introduction of AI mock interviews is particularly important, as it can help graduates develop these critical skills, such as higher-order thinking skills, problem-solving abilities, and communication skills, preparing them for the competitive the labor market.

As highlighted by Bennett (2022), graduates' self-awareness of perceived employability is influenced by factors which are awareness of self and program relative to career, career identity and commitment, perceived program relevance, and career exploration (Bennett et al., 2022). The study examined whether the experimental application had a proactive impact on participants' perceived employability and confidence in relation to study and employability traits including awareness of self and program relative to career; career identity and commitment; perceived program relevance; and career exploration and awareness (Bennett et al., 2022). Participants were tasked with using an AI mock interview technology as part of a career preparation process while actively engaged in a job search. In the context of the experimental intervention, participants were systematically encouraged to use an AI mock interview platform as a supplement to their career preparation. With the exception of this treatment, the career preparation training for the control group was nearly similar to that of the experimental group. Thus, all participants were at the same academic level, had no prior experience with the AI mock interview technology, and were preparing for job interviews in the short term. This pre-test-post-test experimental method study with the control group lasted four weeks. Based on the above discussion, the following hypotheses for this study are proposed:

H1 AI mock interview technology has a significant positive impact on graduate perceived employability.

H1a AI mock interview technology has a significant positive impact on graduates' perceived program relevance.

H1b AI mock interview technology has a significant positive impact on graduates' program and self-awareness of program.

H1c AI mock interview technology has a significant positive impact on graduates' career identity.

H1d AI mock interview technology has a significant positive impact on graduates' reconsideration of commitment.

H1e AI mock interview technology has a significant positive impact on graduates' career exploration and awareness.

H2 The number of interventions for AI mock interviews has a positive impact on graduate perceived employability.

H2a The number of interventions for AI mock interviews has a positive impact on graduates' perceived program relevance.

H2b The number of interventions for AI mock interviews has a positive impact on graduates' program and self-awareness of program.

H2c The number of interventions for AI mock interviews has a positive impact on graduates' career identity.

H2d The number of interventions for AI mock interviews has a positive impact on graduates' reconsideration of commitment.

H2e The number of interventions for AI mock interviews has a positive impact on graduates' career exploration and awareness.

These perceptions significantly impact graduates' confidence and motivation, ultimately affecting their career outcomes. Therefore, there are four main components in the career preparation training based on AI mock interview softwares in this study. First, the professional skills knowledge Q&A interaction component involves graduates in real-time question-and-answer sessions centered on specific occupational knowledge, aiding them in reinforcing essential knowledge and skills relevant to their field. This component can utilize platforms like ChatGPT or Kimi to facilitate engaging and interactive learning experiences. Second, the career identity situational immersion component places graduates in realistic professional scenarios to enhance their sense of career identity and adaptability. In this component, we recommend that participants use softwares such as Zhimianxing, AI Interviewer, and Big Interview, which offer video functionality for human-computer dialogue and simulate real interview scenarios. Third, in the interview performance feedback analysis component, artificial intelligence technology is primarily used to provide detailed feedback for each mock interview, stimulating graduates' reflective and metacognitive skills. This helps them identify their strengths and areas for improvement, allowing for continuous enhancement of their interview preparation skills. In this component, we recommend that participants choose mock interview softwares such as Zhimianxing and Big Interview, which offer timely assessment feedback. Finally, the potential relevant career exploration component aims to guide users in trying out more mock interviews related to their personal traits, helping them gain a comprehensive understanding of the diversity in the job market. This allows them to explore career paths that align with their academic background and personal interests, or to identify and keep alternative career options as a backup choice. In this stage, we ask participants to select a mock interview softwares with a large database that is relevant to the Chinese job market, such as Zhimianxing, AI Interviewer, and Haina Zhitong. These four components complement each other, collectively enhancing students' career preparation abilities and making them more competitive in their future job searches.

3 Methodology

3.1 Research design

This study was a quasi-experimental methods study with a pretest-posttest control group. In this experimental study, participants were randomly and equally assigned to two groups: the AI mock interview treatment group and the control group with no AI intervention. There were 21 participants (50%) in the experimental group and 21 participants (50%) in the control group. Participants included 42 university graduates from Hangzhou, Zhejiang Province, China. The intervention in this study aligns with the goal of enhancing graduates' employability through the application of design-based AI mock interview activities, a key tool for improving employability that participants (graduates) may use in their future job search. In addition, all participants were senior undergraduate students, none of whom had used any AI-based career readiness tools prior to the experiment. None had participated in a job interview before, and all were scheduled to attend a formal job interview within six months, as well as none of the participants were enrolled in additional courses. Thus, participants in both groups were similar in terms of their initial job search readiness, job search needs, and interview experience.

Furthermore, participants in the treatment group were all given the same opportunity to use the AI simulated interview technology during their career readiness training. Thus, although 78 participants were recruited to participate, a total of 42 participants indicated that they could participate in the experiment throughout. Both groups received the same input on the career readiness-based learning activities and tasks. Therefore, there was no learning loss in the control group.

3.2 Participants

Participants were selected based on their responses to an online survey that gathered information about their demographic backgrounds and career preparation experiences. As shown in Table 1, the participants ultimately selected for this experiment were 42 senior students pursuing their undergraduate studies in Hangzhou, China, who had just completed the requirements for their degree. All participants were under pressure to secure employment in the short term and were required to attend job interviews within six months. The high percentage of female participants is due to the researcher's decision to select finance and business graduates, as many finance and business students associate their perceived employability with their actual ability to secure and maintain formal employment (Hogan et al., 2013; Tymon, 2013). And the proportion of female students is generally higher than that of male students in finance and business programs. Additionally, female students were more confident than male students in their sense of professional self-awareness, their career goals, and their commitment to professional responsibilities (Bennett et al., 2022). As a result, they were more willing to participate in the experiment and demonstrated higher levels of engagement and motivation throughout the study. This may be related to the high level of interest in career planning and a stronger sense of commitment to career development among females, as shown by the gender ratio of participants in Table 1.

4 Procedure

In the experimental group, graduates performed mock interview activities for career preparation using AI platforms such as ChatGPT and Kimi. These tasks included setting a career goal, researching interview questions for the targeted position using ChatGPT and other AI resources, participating in interview training with the AI mock interview program, receiving interview feedback and evaluation, conducting mock interview assessments using the AI softwares, and participating in live mock interviews. The AI Apps that the researchers will use in this experiment were introduced a week before the application. Graduates used these apps for various free activities in a career-readiness interview training session. During the first week of the program, graduates were asked to select a specific target career. They then researched their chosen occupation and interacted with ChatGPT and other resources to compile a list of interview questions and answers, along with key points of expertise. During the first week of intensive training, the instructor taught students what to focus on during interviews, such as dress code, behavior, and the approach to answering questions. The instructor also prepared sample interview questions based on the target careers submitted by the graduates and delivered special lectures on answering techniques, how to respond to questions, and what to answer. Additionally, the instructor provided graduates with a list of interview questions tailored to the target careers

Table 1 Demographic information of the participants

Group	N	Female	Male
Experimental group	21	20	1
Control group	21	19	2

they had chosen. In the second week of training, the instructor conducted practical exercises to test the graduates individually on the questions related to their target occupations listed in the previous week. The purpose was to observe the graduates' interviewing behavior, demonstration of their abilities, answering skills, and adaptability, as well as to consolidate their knowledge. In the third week, the instructor asked each participating graduate to practice using the AI mock interview platforms and provided feedback on the results. Based on the feedback from the AI, the instructor gave specific assessments and explanations, aiming to stimulate the graduates' reflection, further improve their self-awareness, and gain a better understanding of the relevant information about their target occupations and interview criteria. During this week, the instructors asked the graduates to complete the task of exploring information about their target careers in class using the AI platforms. This was done to ensure that the graduates could understand the relevant details of the target careers they had chosen, such as hiring standards, skill requirements, specialization restrictions, salary, and more. The fourth week of intensive training was divided into two sessions. In the first session, the instructor used the AI mock interview softwares for live human-computer interaction experience scoring, simulating interviews and assessing the progress made during the first three weeks of training. In the second, the researcher invited two human resources specialists to conduct live simulated panel interviews on-site to assess the employability of the graduates based on the ratings provided by the human resources specialists.

In the control group, graduates were tasked with receiving traditional career readiness training for interview training. This task included target careers, interview preparation, interview training, interview feedback and assessment, and live mock interview assessment. In the first week, students were asked to select a specific target occupation and explain what they knew about it, including employment standards, skill requirements, specialization, salary, and other relevant details. In the first week, students were asked to choose a specific target career and explain their knowledge of it, including employment standards, skill requirements, specialization, salary, and other relevant details. The instructor also shared the list of interview questions from previous years, along with key points to consider and examples for clarification. In the second week, the instructor also conducted practical exercises and observed the graduates' performances, providing feedback on the relevance and reasonableness of their responses. In the third week, the instructor also provided feedback on the results of the exercise without using any AI softwares, highlighting areas of improvement to stimulate the graduates' reflective skills. In the fourth week, the same on-site simulation is conducted to determine the employability of the graduates.

It is important to note that the final on-site mock group interview involved 42 participants. The HR randomly divided the participants into three groups to conduct a group discussion on the same case in a non-leadership group. The HR observed and rated the participants throughout the entire process.

4.1 Instrumentation

Graduate Perceived Employability Scale. This study used Student Self-Assessment of Perceived Employability scale developed by Bennett's (2022), which includes 27 items across four dimensions: Perceived Program Relevance, Program and Self-Awareness, Career Commitment, and Career Exploration and Awareness. Among them, the Career Commitment dimension is further divided into two sub-dimensions, which are Career Identity and Reconsideration of Commitment, with reverse scoring applied to the latter, where lower scores indicate higher commitment. Participants responded to each item on a five-point Likert scale, from 1 (strongly disagree) to 5 (strongly agree). To adapt the scale for the Chinese context, the original English version was translated and back-translated by two professional translators, following Brislin's (1986) guidelines (Brislin, 1986).

Graduate Employability Rating Scale. The items on the scale are adapted from Chiara Succi and Magali Canovi's (2019) scale (Succi & Canovi, 2019). HR directors are required to rate each participant on a scale of 1 to 5 for each of the 20 items, with a total score out of 100 for each participant.

4.2 Measurement

According to the study by Huang, Wei, et al. (2019), when conducting confirmatory factor analysis using IBM SPSS Amos 26 (Huang et al., 2019), it was found that all indicators, except for the item "I am considering the possibility of changing my university major in order to be able to practice another profession in the future," had standardized loadings greater than 0.5 (Yu et al., 2023), with the problematic item having a loading of 0.426. Therefore, it was decided to remove this item and conduct the confirmatory factor analysis again. Due to the fit index NFI = 0.694, which is below 0.7 (Zhao & Yao, 2017), it was decided to remove the item "Figure out which career options could provide a good fit for your personality," which had a standardized loading of 0.516. After removing these two items, the factor loadings ranged from 0.556 to 0.925. After conducting the confirmatory factor analysis again, the fit indices were as follows: $\chi^2/df = 1.741$, CFI = 0.845, RMSEA = 0.095, NFI = 0.705, NNFI = 0.824, RMR = 0.045, and GFI = 0.717. The results of the aggregation validity analysis are presented in Table 2. And the HTMT values were all below 0.85, indicating good discriminant validity among the factors. This suggests that the research data demonstrates strong discriminant validity. The discriminant validity analysis of the scale is presented in Tables 3 and 4. The reliability analysis conducted using SPSS 26 indicated that the overall reliability of this study was 0.700 in the pre-test and 0.873 in the post-test, indicating high internal consistency (Cortina, 1993).

Table 2 AVE and CR indicators

Factor	AVE	CR
Perceived program relevance (PPR)	0.488	0.791
Program and self-awareness (PSA)	0.511	0.879
Career identity (CI)	0.571	0.839
Reconsideration of commitment (RC)	0.600	0.818
Career exploration and awareness (CEA)	0.613	0.916

Table 3 Discriminant validity: pearson correlation and the square root of AVE

	PPR	PSA	CI	RC	CEA
PPR	0.699				
PSA	0.467	0.715			
CI	0.543	0.634	0.756		
RC	0.400	0.484	0.506	0.775	
CEA	0.569	0.566	0.565	0.311	0.783

Table 4 The results of the HTMT (Heterotrait-Monotrait Ratio) analysis

	PPP	PSA	CI	RC	CEA
PPR	-				
PSA	0.558	-			
CI	0.668	0.741	-		
RC	0.506	0.572	0.619	-	
CEA	0.664	0.630	0.645	0.360	-

5 Data analysis

5.1 Comparison of Pre-Test

The data in this study were processed using SPSS 26.0, and it was verified that the pre-test and post-test scores of graduate perceived employability both followed a normal distribution. Before implementing the intervention, it is crucial to ensure that there are no significant differences in variables related to graduate perceived employability between the experimental group and the control group. Otherwise, any conclusions drawn from the intervention might be confounded by differences between the groups rather than reflecting the effect of the intervention itself. Existing literature indicates that variables such as gender, age, place of origin, annual family income, social engagement can influence graduates' self-awareness of perceived employability (Huang et al., 2021; Zhao & Wu, 2022). The results of the descriptive statistics analysis indicated that the relevant variables—place of origin, family annual income, and social participation—have a normally distributed effect on employability. And prior to the implementation of the experiment, there were no significant differences between the two experimental groups in terms of place of birth, family income, and social participation, which suggests that these variables do not significantly affect GPE. The analysis results are shown in Table 5.

5.2 Changes in graduate perceived employability

Descriptive statistics were analyzed for the GPE scale scores, and independent samples t-tests were conducted to determine whether the intervention had an impact on GPE, as shown in Table 6. The effect of the pre-test scores was also considered, and an analysis of covariance (ANCOVA) was used to compare the two groups at the post-test, controlling for pre-test scores, as shown in Table 7.

The results showed that the AI mock interviews intervention significantly improved the GPE. After controlling for pretest scores, the perceived employability of experimental group was significantly higher compared to the control group, confirming the

Table 5 The result of repeated measures ANOVA analysis

		Group A	Group B	F	Sig.
Place of Origin	Rural	5	7	0.502	0.483
	Urban	16	14		
Annual Family Income	< CNY 30,000	2	9	0.463	0.504
	> CNY 30,000 and < CNY 500,000	14	10		
	> CNY 500,000	5	2		
Social Engagement	Internship engagement	12	10	0.056	0.815
	Club activities engagement	3	3		
	Social networking length	3	6		
	Student-related matters	3	2		

Table 6 The independent samples T-tests *Result of GPE*

	Experimental group (A)		Control group (B)		95% Confidence Interval of the Difference	Sig.
	Mean	Std. Deviation	Mean	Std. Deviation		
Pre test	3.43	0.507	3.43	0.507	-0.316, 0.316	0.002
Post-test	4.19	0.602	3.62	0.498	-0.916, -0.227	

Table 7 Covariance (ANCOVA) result of graduate perceived employability

Source	R^2	df	F	Sig.
PRE	0.385	1	8.402	0.006
Experimental group		1	13.332	0.001

positive impact of the intervention. These findings suggest that AI mock interviews can be an effective tool for improving GPE.

5.3 Dimensions analysis

During the intervention, the experimental and control groups received the same content of career readiness training from the same instructor, except that the experimental group's training incorporated AI mock interview technology. The training sessions for both groups were scheduled twice a week, with each session comprising 30 min of instruction and 1 h of interactive training. To specifically analyze the impact of AI mock interviews on the dimensions of GPE, ANCOVA was conducted for each dimension in this study. Since previous data indicated that pre-test scores had a significant effect on post-test scores, it was necessary to examine the impact of the AI mock interview intervention on the dimensions of Graduate Perceived Employability while controlling for pre-test scores. The results are shown in Table 8.

In terms of the specific dimensions of GPE, after controlling for the effects of pre-test scores, the AI mock interview intervention had a significant positive

Table 8 ANCOVA on the specific dimensions

		Experimental group (A)		Control group (B)		F	Sig.
		Mean	Std. Deviation	Mean	Std. Deviation		
PPR	Pre-test	3.67	0.577	3.43	0.507	0.468	0.498
	Post-test	4.14	0.573	3.52	0.512	11.753	0.001
PSP	Pre-test	3.62	0.590	3.43	0.507	1.251	0.270
	Post-test	4.10	0.625	3.62	0.498	6.264	0.017
CI	Pre-test	3.62	0.669	3.57	0.507	0.000	0.984
	Post-test	4.24	0.625	3.57	0.598	12.146	0.001
RC	Pre-test	3.52	0.680	3.52	0.602	0.630	0.432
	Post-test	4.05	0.740	3.76	0.539	2.027	0.163
CEA	Pre-test	3.19	0.602	3.43	0.507	0.102	0.751
	Post-test	4.19	0.750	3.33	0.577	15.530	0.000

impact on several dimensions, particularly in PPR, PSP, CI, and CEA. Compared to the control group, the experimental group showed a significant increase in posttest scores, while no significant change was observed in the RC. This may be due to the fact that AI mock interviews are primarily focused on enhancing graduates' interviewing skills, self-exploration, and career awareness, whereas reconsidering their commitment at the end of the program is something that few students are likely to engage within a short period of time (Bennett et al., 2022). In addition, the experimental intervention in the current study lasted only one month and may not have fully captured the impact of AI mock interviews on the RC. Reconsidering career commitment could be a long-term cognitive and reflective process that requires deeper thought and practical experience, and the short duration of the mock interviews may not have provided enough time to influence this dimension. Therefore, the impact of the AI mock interview intervention on the RC may need to be considered in further research in a more long-term longitudinal study.

5.4 Relationship between number of interventions and graduate perceived employability

During the entire intervention process of the experiment, we conducted a total of 8 training sessions, twice per week. However, several participants were unable to attend the AI mock interview training sessions due to health issues or other commitments, which may have resulted in different numbers of interventions for the experimental and control groups. And the graduates reported that they had not used any AI mock interview tools prior to the intervention experiment. Therefore, does the number of interventions have a significant effect on graduate perceived employability improvement? To address this issue, a regression analysis was conducted with "the number of interventions for experimental group students" as the independent variable, controlling for the effect of pre-test scores, and the GPE score as the dependent variable. Table 9 presents the results of the regression analysis, $F(2, 20) = 17.188$, $p = 0.000$. which indicates that the pre-test scores did not have a significant effect on the post-test scores while the regression equation was marginally significant. There is a significant linear relationship between the

Table 9 Linear regression analysis results

	Sum of Squares	df	Mean Square	F	Sig.	R^2
Regression	4.751	2	2.375	17.188	0.000	0.656
Residual	2.488	18	0.138			
Total	7.238	20				

improvement in graduate perceived employability and the number of interventions, suggesting that the frequency of interventions affects graduate perceived employability.

5.5 Graduate employability scores from the HR perspective

At the end of the experiment, the researchers invited two HR experts to conduct live mock interviews with 42 graduates, assessing and scoring their employability performance. The findings showed that the two HR experts evaluated the participants' employability based on similar criteria, with minimal differences in scores and a high correlation (Pearson's correlation coefficient = 0.975, $p = 0.000$). Further independent samples t-tests revealed a significant difference between the experimental and control groups in terms of employability scores ($p = 0.000$), with a 95% confidence interval ranging from 9.227 to 13.058, as shown in Table 10. In addition, the data were tested for normality, and the results confirmed that the assumption of normal distribution was met, thereby ensuring the validity of the statistical analysis.

Regarding the scores from the HRs' assessment of the employability performance dimensions of the participating graduates, significant differences between the experimental and control groups include: communication skills, being committed to work, team-work skills, being tolerant to stress, analysis skills, continuous improvement skills, adaptability to changes skills, self-awareness skills, contact network skills, creativity/innovation skills, culture adaptability skills, management skills, leadership skills. However, no significant differences were observed between the two groups on the following dimensions: learning skills, results orientation skills, customer/user orientation skills, decision making skills, being professionally ethical, conflict management & negotiation skills, life balance skills. Perhaps this will be the focus of further research.

6 Discussion and conclusion

Self-confidence plays a crucial role in graduates' awareness, motivation and behavior. Although self-reported assessments may be subject to cognitive biases, Bandura (1993) has pointed out that individuals' self-efficacy beliefs often serve as better predictors of their performance than their actual abilities (Bandura, 1993). Therefore, in line with the principles of CCT, an individual's performance and adaptability in the workplace are closely linked to how they understand and construct their career identity (Savickas, 2012). By helping graduates understand their strengths and the alignment between career readiness and career require-

Table 10 HRs' evaluation of graduates' employability performance

Dimensions	Experimental group (A)		Control group (B)		t	Sig.
	Mean	Std. Deviation	Mean	Std. Deviation		
Communication Skills	4.24	0.726	3.24	0.983	5.303	0.000
Being Committed to Work	4.24	0.532	3.43	0.668	6.143	0.000
Team-Work Skills	3.71	0.708	3.33	0.570	2.715	0.008
Learning Skills	4.00	0.698	3.81	0.671	1.274	0.206
Being Tolerant to Stress	4.21	0.606	3.38	0.854	5.156	0.000
Analysis Skills	4.21	0.682	3.57	0.703	4.252	0.000
Continuous Improvement Skills	4.50	0.707	3.64	0.692	5.614	0.000
Results Orientation Skills	3.93	0.601	3.67	0.687	1.861	0.066
Adaptability to Changes Skills	4.52	0.594	3.14	0.718	9.602	0.000
Customer/User Orientation Skills	3.76	0.576	3.74	0.497	0.203	0.840
Self-Awareness Skills	4.31	0.604	3.48	0.994	4.644	0.000
Contact Network Skills	3.81	0.773	3.48	0.740	2.019	0.047
Creativity/Innovation Skills	4.33	0.816	3.40	1.037	4.559	0.000
Decision Making Skills	4.19	0.707	3.98	0.680	1.416	0.161
Being Professionally Ethical	4.19	0.505	4.05	0.795	0.983	0.329
Conflict Management & Negotiation Skills	3.69	0.950	3.29	1.175	1.737	0.086
Culture Adaptability Skills	3.74	0.701	3.38	0.661	2.403	0.018
Management Skills	3.86	0.899	2.83	0.762	5.628	0.000
Leadership Skills	3.52	0.671	3.00	0.765	3.335	0.001
Life Balance Skills	3.33	0.902	3.43	1.151	−0.422	0.674

ments early on and throughout their career development programs, higher education institutions can assist them in developing overall confidence and a more realistic self-awareness, since graduates' self-perceptions of employability are often skewed by misinformation, insufficient exposure to the industry, or inflexible career decision-making (Bennett et al., 2022; Fearon et al., 2018; Jackson, 2018).

In addition, in this study, live mock interview ratings from two HR experts were used to assess graduates' employability. This type of assessment effectively eliminates the cognitive biases that can occur in self-reported evaluations, as the ratings from HR experts are typically based on more objective criteria and exhibit a high level of professionalism and consistency (Heijde & Van Der Heijden, 2006; Succi & Canovi, 2019). In the results of the study, significant differences in perceived employability were demonstrated between the AI intervention group and the control group, and graduates in the experimental group received higher ratings on a number of employability dimensions. This suggests that the AI intervention not only helps to improve GPE, but also enhances their competitiveness in interviews and the job market. This is in line with the findings of many previous studies (Lewton & Haddad, 2024; Pompedda et al., 2020; Uppalapati et al., 2025). Considering the financial and time constraints of the study, future research could further explore the significant differences in HR scores across various employability dimensions and incorporate qualitative research to gain deeper insights into graduates' perceptions and experiences of the AI intervention. Meanwhile, consideration can be given to how this intervention can be extended to a wider sample and more real-world contexts to validate its generalisability and long-term effects.

An important limitation of this study is the small sample size, which is limited to Hangzhou, Zhejiang Province. This limitation is particularly prominent in AI-driven mock interview systems, as small sample size data usually affects the training effect of the model, which may result in a limited ability to generalize the model to real-life scenarios. This phenomenon is similar to the "data imbalance" problem in deep learning, where the data for certain categories is insufficient, potentially leading to low prediction accuracy for these categories (Chen et al., 2024). However, the latest AI mock interview tools employ various techniques that can effectively mitigate the negative effects of small data samples. For example, Generative Adversarial Network (GAN) and Transfer Learning can enhance the training set by generating more diverse simulated data, thereby improving the model's learning performance even with limited samples (Chen et al., 2024). Additionally, techniques such as Self-Adaptive Adaptive Convolutional Neural Networks (SAACNN) and auto-encoder Wasserstein generative adversarial networks (AEWGAN) can further optimise the training process of the model to enhance its performance in small sample environments and effectively reduce the risk of overfitting (Chen et al., 2024). Furthermore, to compensate for the lack of data, researchers have used a variety of mock interviews to reliably assess the feedback during the experiments (Pompedda et al., 2020; Uppalapati et al., 2025). Nevertheless, we must acknowledge that the effect remains limited. In order to improve the generalisability and reliability of the model, future research should still consider expanding the sample range to cover diverse sample data from different regions and countries. This will not only contribute to improving the training quality of the model, but also enhance its generalisability and operability in practical applications.

Besides this, the current study mainly focuses on the short-term effects of AI mock interviews, and future research should assess its long-term effects through a longitudinal research design. And individual differences such as academic background and personality traits may have an impact on the effectiveness of AI mock interviews, and future research should explore these moderating factors and analyze the differences in effects across individuals, as well as the practical application of AI mock interviews and graduates' acceptance of them may affect the generalizability of the findings. Therefore, future studies should evaluate these factors within real-world contexts. To gain a more comprehensive understanding, future research could adopt a mixed-methods approach, combining qualitative research with quantitative data through interviews or focus group discussions. This approach would help explore the specific mechanisms through which AI mock interviews impact GPE, such as their effect on self-efficacy and employment confidence. With these improvements, future research will provide more in-depth theoretical and practical support for the application of AI in graduate career planning. Overall, this study has significant empirical value for the field of career planning education. By examining the effects of AI mock interviews on GPE and assessing the real-world performance of graduates who received AI interventions in interview scenarios, this study highlights the potential of AI mock interview technology to enhance graduates' readiness for employment. It also provides a valuable practical foundation for future innovations in vocational guidance and career planning within higher education, as well as for fostering adaptable, competitive talent in the field of education. This aligns well with the broader context of AI and addresses a long-standing social issue relevant to the Industry 4.0 era.

Author contributions All authors contributed to the study conception and design. Material preparation and data collection were performed by Wang, Dong. The first draft of the manuscript was written by Shi, Wei and all authors commented on previous versions of the manuscript. All authors read and approved the final manuscript.

Data availability The datasets used during the current study available from the corresponding author on reasonable request.

Declarations

Competing interest The authors have no competing interests.

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