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AI-EMPOWERED CAREER PLANNING IN CHINESE HIGHER EDUCATION: THE IMPACT OF AI-BASED CAREER READINESS ON GRADUATES' EMPLOYABILITY

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Abstract:

The impact of artificial intelligence (AI) on university graduates' career preparation and employability in higher education has increased in recent times. However, research on the application of artificial intelligence (AI) in the Chinese higher education context, particularly in the resource-constrained province of Gansu, remains notably scarce. Hence, this study aims to address this gap and test the relationship between behavioural beliefs – career planning – perceived employability based on the stimulus-organism-response (SOR) framework and social cognitive career theory (SCCT). This study was conducted over a period spanning October 2024 to September 2025, and data was collected from 770 senior students pursuing a bachelor's degree at a finance and economics university in Gansu Province and analysed using structural equation modelling (SEM). The findings indicate that graduates' behavioural beliefs about the usefulness of AI significantly influence their employability, with career planning playing a crucial mediating role. Although AI applications do not directly impact employment, they indirectly influence university graduates' confidence in finding a job and their competitiveness in the market. This study extends SCCT's applicability within technological contexts and enriches SOR theory's explanatory power regarding multi-level mechanisms between environmental stimuli and responses. Meanwhile, it offers fresh perspectives and insights for reforming career planning in higher education regarding AI integration in China.

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Keyword:

Artificial Intelligence (AI), Behavioural Beliefs Of AI, Career Planning, Graduate Perceived Employability, Higher Education

Introduction

The advent of the knowledge economy has transformed an integral part of daily life, while intensifying global competition has led to widespread recognition among policymakers and scholars of the critical importance of employability (Peeters et al., 2017). In a rapidly changing employment landscape, university graduates face significant uncertainty and intense competition as they transition from school to the workforce. Enhancing university students' employability, particularly their subjective perception of their own competitiveness in the labour market, has become a central issue in higher education research and practice. This is because perceived employability not only reflects students' level of career readiness but also directly influences their employment confidence and job-seeking behaviour, which are widely regarded as significant predictors of employment outcomes (Gupta & Ansari, 2023; Yizhong et al., 2017).

Meanwhile, globalisation and digitalisation of Industry 4.0 are profoundly reshaping traditional career-planning models in higher education (Nurjanah et al., 2022). The diverse requirements of contemporary university students for personalized development, digital proficiency, and interdisciplinary competencies in an intricate and perpetually evolving labour market are progressively inadequately addressed by the dependence on conventional pedagogical approaches, internship frameworks, and career counselling (Bejaković & Mrnjavac, 2020; Shi & Wang, 2025). For example, in 2024, although there were 11.79 million university graduates in China, surveys indicated that the employment rate was only about 55.5%, meaning that nearly half of graduates faced difficulties in finding jobs (Frontier, 2024). Meanwhile, among these nearly 12 million graduates, 54% reported a lack of clear career objectives (Recruitment of Zhilian, 2024). Furthermore, a survey on the state of youth career planning in 2023 revealed that 49.5% of respondents expressed low satisfaction with the career planning services provided by their universities (People's Data Research Institute & School of Journalism and Communication, 2023). These data are sufficient to demonstrate the limitations of the traditional career planning model. To fix these problems, generative artificial intelligence (AI) tools are being used more and more in higher education to help with things like resume optimization, career matching, mock interviews, and job counseling (Shi & Wang, 2025). Such tools not only provide students with efficient information and resources but may also reshape their perceptions of their own capabilities and career prospects (ZHANG & Yu Francis, 2025). It must be admitted that the advancement of generative AI has opened new possibilities for career preparation and planning. However, existing research predominantly focuses on teaching or learning contexts. Systematic empirical studies examining the mechanisms through which generative AI enhances university students' perceived employability by facilitating career planning remain insufficient. The research by Li et al. (2025) primarily focused on examining the mediating role of AI literacy and attitudes through psychological outcomes, without delving into the mediating mechanisms of career planning in optimising employment confidence (R. Li et al., 2025). Herath et al. (2024) noted through a literature review that there remains a lack of systematic empirical testing examining how generative AI and career planning jointly influence university graduates' perceived employability (Herath et al., 2024). Furthermore, while numerous higher education institutions and academic journals have recognised the potential of generative AI in learning and career preparation, these explorations largely remain at the level of policy interpretation, practical guidance, or preliminary surveys (Falebita & Kok, 2025; Jia & Tu, 2024). It must be acknowledged that there is a significant lack of systematic, rigorous non-experimental empirical research.

This study aims to address existing research gaps by conducting an empirical analysis of the practical application of AI in career planning for university students. Using a pilot institution in Gansu Province as a representative case study, this research not only provides theoretical support for the application of generative AI within higher education but also offers practical recommendations for higher education institutions in China and beyond on how to effectively utilise this technological tool to enhance graduates' employability and career readiness.

Literature Review

Theoretical Framework

Stimulus–Organism–Response (SOR) Model

The Stimulus–Organism–Response (SOR) model, proposed by Mehrabian and Russell (1974), explains how external environmental factors ultimately trigger behaviour or outcomes through changes in an individual's internal cognition, emotions, and capabilities (Jacoby, 2008; Mehrabian, 1974). The SOR framework serves not only as an explanatory tool but also provides a clear pathway for the logical construction of the theoretical model in this study. Specifically, artificial intelligence (AI) tools/technologies and their application in career preparation are regarded as external stimuli (S), offering graduates a novel learning and development environment. This stimulus leads graduates to create internal organismic variables (O), which are mostly behavioral beliefs about AI. These beliefs are their thoughts and feelings about how useful and easy AI tools and technologies are for preparing for a career and planning a career, which includes the cognitive and motivational aspects of setting goals, designing pathways, and taking action. These organismic variables serve as mediating mechanisms, explaining how external technology is internalised as individual psychological and behavioural resources. Ultimately, the reaction (R) manifests as two categories of outcomes, namely proximal and distal. Proximal outcomes represent graduate perceived employability, denoting graduates' subjective perceptions of their own competitiveness in the labour market. Distal outcomes encompass actual employment outcomes, covering post-graduation employment status, employment quality, and career development levels. This study focuses on the proximal reaction effect of perceived employability, while treating distal employment outcomes as a theoretical extension and value orientation of the research.

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Social Cognitive Career Theory (SCCT)

Within the context of higher education, SCCT offers a significant theoretical perspective for understanding university graduates' career readiness and employability. Social Cognitive Career Theory (SCCT), proposed by Lent, Brown and Hackett in 1994 (Lent et al., 1994), is a career development framework developed from Bandura's social cognitive theory (Bandura, 1986). This theory posits that an individual's career development process is jointly driven by three core elements, which are self-efficacy, outcome expectations, and personal goals, and is continuously influenced by contextual factors and learning experiences (Wang et al., 2022). This theory considers the social construction of career identity and decision-making, including the influence of proximal and distal factors and the role of psychological capital (Bennett et al., 2022). Building upon the SOR framework, SCCT provides a more detailed interpretation of the O-layer mechanism. Within the SCCT framework, career planning functions both as an outcome of the interaction between cognitive beliefs and the external environment, and as an intermediary process that facilitates career development and enhances employability (Kleine et al., 2023).

Graduate Perceived Employability

Graduate Perceived Employability (GPE) has become an increasingly important area of study in higher education and career development in recent years. Unlike traditional measures of objective employment outcomes, such as employment rates or salary levels, perceived employability places greater emphasis on individuals' subjective assessments of their competitiveness within the labour market (De Cuyper et al., 2014; Rothwell & Arnold, 2007). Their self-awareness reflects not only self-evaluation of their knowledge, skills, and attributes, but also their sensitivity to external environments and career opportunities (Ho et al., 2022; Jackson & Tomlinson, 2020).

On an intrinsic level, GPE is widely considered a multi-dimensional psychological construct. Existing research indicates that it typically encompasses aspects such as self-awareness and career-related planning, career identity and commitment, perceived relevance of career planning, and career exploration and awareness (Bennett et al., 2022). These dimensions not only reveal distinct psychological and behavioural tendencies among graduates during career preparation but also provide a structured framework for understanding their career development trajectories. For instance, strong career planning self-efficacy is generally associated with greater initiative and more proactive career exploration (Kleine et al., 2023). Meanwhile, career commitment signifies an individual's steadfastness in pursuing their goals, even amidst unpredictable circumstances (Spurk et al., 2022).

Prior research concerning perceived employability has predominantly been underpinned by Social Cognitive Career Theory (SCCT) (Bennett et al., 2022; Lent & Brown, 2013). This framework highlights the significance of personal attributes like self-efficacy and career adaptability, educational experiences such as course quality and internship opportunities, and external factors including labour market conditions and organizational support (Clarke, 2017; Fugate et al., 2004; Tomlinson, 2017). However, against the backdrop of rapid digitalisation and AI development, traditional influence mechanisms face new challenges. AI technologies not only demonstrate unique advantages in accessing career information, interview training, and personalised feedback, but may also reshape the developmental pathways of perceived employability by altering how individuals engage with their environment (Shi & Wang, 2025;

Zhan et al., 2024). While has been demonstrated that graduates possessing higher levels of perceived employability are more likely to exhibit confidence, initiative, and adaptability during the job search process, thereby securing superior career opportunities (Jackson & Tomlinson, 2020). Perceived employability is widely regarded as a significant predictor of actual employment outcomes, rendering it highly valuable in both theory and practice (Gupta & Ansari, 2023). Nevertheless, whilst research on perceived employability has advanced in China, it has largely concentrated on macro-level or institutional factors, including educational quality, industry-academia collaboration, and labor market conditions (Hong-chao et al., 2020; Jia & Tu, 2024).

Behavioural Beliefs

In applied research concerning artificial intelligence (AI) and educational technology, perceived ease of use (PEU) and perceived usefulness (PU) are widely recognized as pivotal individual cognitive variables. Although originating from the Technology Acceptance Model (TAM) (Davis, 1989; Venkatesh et al., 2003; Wixom & Todd, 2005), these concepts can equally be understood within different theoretical frameworks, particularly the Stimulus–Organism–Response (SOR) model, as core psychological responses to external stimuli such as AI tools and digital platforms (Pan et al., 2024).

PEU reflects graduates' subjective assessment of how simple a technology is to operate (Davis, 1989). Research by Alwi & Khan (2025) revealed that perceived ease of use significantly impacts students' readiness to adopt AI tools. Students who find these tools easy to operate are more inclined to incorporate them into their studies, thereby enhancing their overall capabilities (Alwi & Khan, 2025). Similarly, in a study integrating AI into Lebanese accounting curricula, Abdo-Salloum and Al-Mousawi (2025) proposed that technological readiness influences student AI adoption through the mediating effect of perceived ease of use (Abdo-Salloum & Al-Mousawi, 2025). This suggests that perceptions of ease can lower psychological barriers to new technologies, speeding up their adoption. PU highlights graduates' evaluations of a technology's effectiveness in reaching their goals (Davis, 1989). Numerous studies based on the Technology Acceptance Model (TAM) have consistently shown that when users perceive a tool as "useful", it increases their willingness to adopt and continue using it, leading to improved learning outcomes or performance (Legramante et al., 2023; J. Li et al., 2025; Wixom & Todd, 2005).

However, existing research has yet to empirically examine the influence of behavioural beliefs (PEU and PU) on perceived employability. Within career planning and employment preparation contexts, when AI tools are perceived as having low learning costs and intuitive operation, graduates are more likely to overcome psychological barriers and actively incorporate them into career exploration and skill enhancement processes (Dwianto et al., 2024). These positive experiences lower the psychological barrier to technology adoption, empowering graduates to more effectively utilize digital resources in bolstering their employability. Also, if graduates believe AI technologies can deliver more precise employment information, improve career decision-making quality, or create additional job opportunities, they become more inclined to rely on these tools, thereby strengthening their confidence in their own employability (Lewton & Haddad, 2024; Shi & Wang, 2025). Thus, this study proposes the following hypotheses:

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H1: There is a significant influence of perceived ease of use on graduate perceived employability among university graduates in China.
H2: There is a significant influence of perceived usefulness on graduate perceived employability among university graduates in China.

It is noteworthy that existing research indicates PEU and PU are not independent constructs but rather mutually reinforcing (Davis, 1989; Wixom & Todd, 2005). As Wixom and Todd (2005) suggested, technological tools that are simple to operate are often further perceived as "useful", thereby enhancing an individual's motivation to use them (Wixom & Todd, 2005). This mechanism holds particular significance in the realm of AI-based career planning. Graduates, often constrained by limited resources and time, simultaneously assess both the feasibility and the practical value of these tools (Tulinayo et al., 2018). Based on this, hypothesis can be proposed:

H3: There is a significant influence of perceived ease of use on perceived usefulness among university graduates in China.

Career Planning

Career planning (CP) is widely recognized as a crucial psychological and behavioral factor in university graduates' career development. It not only indicates an individual's clarity and readiness concerning future career goals but also influences their self-efficacy and employability to some extent (Kleine et al., 2023). Jackson and Tomlinson (2020) state that CP involves setting goals and formulating strategies to achieve one's individual career aspirations (Gould, 1979). It is a key component of the highly respected DOTS model of career competencies, which covers decision-making, opportunity awareness, transition learning, and self-awareness (Watts, 1977).

Existing research indicates that career planning within higher education settings is often significantly influenced by external technological support and information resources (Antonio & Chiesa, 2024; Huang, 2025). For instance, Huang (2025) employed an AI-based personalized teaching system, integrating online resources, industry databases, and cloud platforms. The study revealed that such systems significantly boost the scientific rigor and satisfaction levels associated with university students' career planning (Huang, 2025). However, empirical research directly examining whether behavioural beliefs regarding AI can predict career planning among university graduates remains relatively scarce. Among Taiwanese university students, a study demonstrated that efficacy expectations and usage intentions exhibited a significant positive correlation with career adaptability (Tang et al., 2025). Although this finding does not directly focus on career planning, it suggests that behavioural beliefs regarding AI in career preparation may enhance graduates' resilience and adaptability towards future career development. Therefore, this study preliminarily posits that when AI is integrated into career services and employment guidance contexts, graduates' behavioural beliefs regarding AI tools (such as PEU and PU) are likely to influence the proactiveness and systematic nature of their CP.

In addition, previous research has consistently highlighted the close connection between career planning and perceived employability (Ho et al., 2022; Jackson & Wilton, 2017; Li & Fan, 2025). It is well established that career planning aids graduates in establishing clear professional objectives and formulating actionable strategies. This, in turn, motivates them to

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deliberately acquire knowledge and skills pertinent to their desired roles throughout their academic pursuits. This purposeful preparation not only enhances graduates' confidence in future employment but also strengthens their subjective perception of personal competitiveness (Jackson & Tomlinson, 2020; Lewton & Haddad, 2024). Following this logic, it can be inferred that CP may act as a mediating mechanism between external technological stimuli (such as AI tools/platforms) and GPE.

Based on the above discussion, this study proposes the following hypotheses:

H4: There is a significant influence of perceived ease of use on career planning among university graduates in China.

H5: There is a significant influence of perceived usefulness on career planning among university graduates in China.

H6: There is a significant influence of career planning on graduate perceived employability among university graduates in China.

H7: There is a significant mediating effect of career planning on the relationship between perceived ease of use and graduate perceived employability among university graduates in China.

H8: There is a significant mediating effect of career planning on the relationship between perceived usefulness and graduate perceived employability among university graduates in China.

Figure 1 presents the conceptual framework of this study. Within this framework, AI is regarded as an external stimulus variable, whose ultimate impact manifests in university graduates' employment outcomes. Consequently, employment outcomes are defined as the distal reaction, while perceived employability serves as the proximal reaction, directly reflecting individuals' self-perceptions regarding their employment readiness and competitiveness. This study introduces two key variables of behavioural beliefs, namely PEU and PU. PEU is posited as a antecedent variable of PU. Moreover, CP acts as a mediator. Specifically, it mediates the relationship between PEU and GPE, and similarly, it mediates the relationship between PU and GPE. This framework clarifies the mechanisms by which AI tools impact employment outcomes in higher education settings.

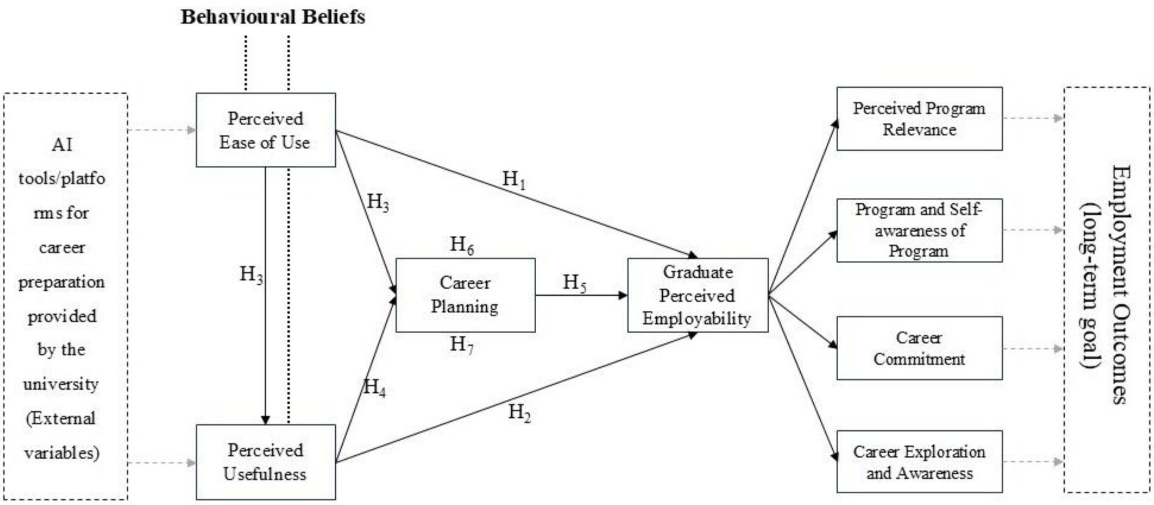

Figure 1: Conceptual Framework of This Study

Source: author's own notes.

Methodology

Participants

For this study, a convenience sampling method was utilized, with over 5,000 final-year students at a finance and economics-focused undergraduate institution in Gansu Province, China, received a questionnaire. Their ages range from 21 to 23 years old. These students all shared backgrounds in finance and economics disciplines, including, but not limited to, accounting, business administration, and international trade. During questionnaire design, the authors collaborated with two English language specialists to ensure the clarity and appropriateness of the questions (Bracken & Barona, 1991). Based on their feedback, improvements were made to the Chinese wording to eliminate any potential ambiguities or misunderstandings. Approval has been obtained from the institutional ethics review board for this study. 812 questionnaires in all were gathered. A valid response rate of 94.83% was obtained by analyzing 770 valid questionnaires after 52 that did not fit the study criteria were eliminated. Table 1 displays the respondents' basic demographic information.

Table 1： Demographic Characteristics of Respondents

Variable	Classification	Frequency	Percent
Gender	Male	182	23.64
	Female	588	76.36
Place of birth	Rural	262	34.03
	Unban	508	65.97
Social engagement	No	476	61.82
	Yes	294	38.18
AI Utilization	1 time	488	63.38
	2-3 times	238	30.91
	4-5 times	13	1.69
	More than 5 times	31	4.02
Total		770	100.00

Source: author’s own notes.

Procedure

This research formally commenced in October 2024, with the overall study cycle spanning nearly one year. Data extraction and final analysis were completed in September 2025. The study focused on the application of AI technology in the career preparation of university graduates, specifically examining how AI tools can be systematically integrated into existing career planning and employment guidance systems within higher education institutions to enhance graduates' employability. During the preparatory phase (2024.10-2024.12), the investigators finalized the study design, revised the measurement instruments, and coordinated with participating higher education institutions. It is worth highlighting that before this study commenced, higher education institutions in Gansu Province had not systematically introduced AI tools at either the institutional level or within teaching practices for graduate career preparation or employability development. The choice of a finance-focused university stems from the observation that many students in finance, economics, and business disciplines tend to equate their perceived employability with their actual ability to secure and retain formal employment (Hogan et al., 2013; Tymon, 2013). The university is the sole undergraduate institution in Gansu Province that specialises in finance and economics. In light of this, the university launched a pilot application and established a strategic partnership with the company that created the AI career preparation tool, AI-ZhiMianXing. This initiative established it as the first higher education institution in Gansu to formally employ AI for graduate career preparation. This collaboration provided a genuine, stable, and sustainable application context for the present research.

During the formal intervention phase (2025.1-2025.8), this study systematically integrated AI tools into employability development within the existing career planning curriculum and employment guidance framework. This was achieved through a phased, progressive training design. AI-ZhiMianXing served as the primary career preparation tool throughout the training process, supporting key stages including position analysis, competency matching, resume optimisation, and simulated interviews. Concurrently, general-purpose AI tools such as DeepSeek and Doubao were employed as supplementary resources for career information retrieval and text generation support.

Specifically, the first phase is familiarisation with AI tools and integration with career planning. Building upon the university's existing career planning curriculum, this phase guides students to systematically learn the core functionalities of AI tools for career preparation. It helps graduates understand the auxiliary role of artificial intelligence in career decision-making support, competency assessment, and employment readiness, while establishing their acceptance and initial belief in AI-assisted career preparation. The second stage involves specialised employment skills training integrated with AI. Once students have mastered basic operations, the research further embeds AI tools deeply into the institution's routine employment guidance processes. For instance, after completing traditional resume writing and position analysis tasks, participants utilise AI tools for targeted optimisation. During mock interview training, AI-powered platforms like AI-ZhiMianXing facilitate structured and situational interview practice, with graduates reflecting on and refining their responses under teacher guidance based on AI feedback. This phase emphasised the synergistic role of AI tools alongside teacher guidance. The third phase involved personalised integration and autonomous practice. Here, graduates independently selected and flexibly applied AI-ZhiMianXing alongside other auxiliary tools, tailoring their use to individual professional backgrounds, career objectives, and skill sets. Instructors primarily provided guidance and support, helping graduates develop self-regulation skills in AI usage to facilitate the transition from standardised training to personalised employability development.

Following completion of the phased training, data extraction and collation commenced uniformly in September 2025. This systematically gathered graduate data concerning behavioural beliefs (PEU and PU) regarding AI tools for career preparation, career planning, and perceived employability. Conducted within the authentic teaching and career guidance context of the first AI career readiness pilot institution in Gansu Province, this research provides regionally representative and practically valuable empirical evidence for exploring AI-enabled employability development among university graduates.

Measures

All measurement instruments employed in this study utilise 7-point Likert scales (1 = Strongly disagree; 4 = Neutral; 7 = Strongly agree). The measurement of behavioural beliefs utilises the

12-item scale developed by Davis (1989), comprising six items each for PU and PEU (Davis, 1989; Noral Hidayah, 2025). CP was assessed using an adapted, five-item version of the Career Development Inventory–Australia (CDI-A) by Jackson & Tomlinson (2020) (Jackson & Tomlinson, 2020). GPE was assessed using the scale developed by Bennett and Ananthram (2021). This 27-item instrument evaluates graduates' perceptions of their strengths and challenges regarding employability, alongside their perceived alignment between their learning experiences and employability (Bennett & Ananthram, 2021). It should be noted that the "reconsidering commitment" item within the Career Commitment (CC) dimension was reverse scored (Bennett et al., 2022). All scales comprised self-report measurement instruments.

Data Analysis

To analyze the data and test the research model, SmartPLS 4.0 was employed. The process unfolded in two stages: initially, the measurement model underwent evaluation to confirm its reliability and validity. Subsequently, the structural model and its hypotheses were assessed using PLS-SEM, a method adept at simultaneously examining multiple relationships. This latter analysis leveraged a bootstrapping technique with 5,000 resamples (Joseph F. Hair et al., 2021).

Findings

This study employed partial least squares structural equation modeling (PLS-SEM) for its analysis. Data for both endogenous and exogenous variables were collected from the same participants using a cross-sectional research design. It was necessary to address common method bias and multicollinearity. The Harman one-factor test was used to assess common method bias (Harman, 1976). The results of this study indicate that the CMV value is less than 50%. Therefore, no common method bias exists in this study. The variance inflation factor (VIF) was employed to examine multicollinearity. The VIF values for all latent variables were below 5.0, indicating that multicollinearity is not significant (Joseph F. Hair et al., 2021).

Measurement Model

Table 2 shows the reflective measurement model evaluation. In the evaluation of the measurement model for this study, the outer loadings (OL) output by SmartPLS were used as estimates for the standardized factor loadings. The findings showed that, among the 44 measurement items, all items except CC19 had OL values greater than 0.70 (ranging from 0.709–0.905). Following the recommendation of Joseph F. Hair et al. (2021) that OLs between 0.40–0.70 are still acceptable in exploratory research, CC19 (OL = 0.651) was retained (Joseph F. Hair et al., 2021). The Cronbach's alpha coefficients for all latent variables in the measurement model were above 0.900, falling within a range of 0.913 to 0.972. These values are consistent with Lomax's (2004) recommendations, confirming acceptable item reliability and sufficient construct reliability for the scales (Lomax, 2004). Confirmatory factor analysis (CFA) provided empirical support for the convergent and discriminant validity of the measurement. Convergent validity was first assessed by evaluating composite reliability (CR). The CR values for all variables in this study exceeded 0.90.

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Table 2: Measurement Model Assessment

Constructs		Items	Loadings	VIF	AVE	CR
Behavioral beliefs (BBS)	PEU	PEU1	0.827	2.377	0.708	0.936
		PEU2	0.835	2.487		
		PEU3	0.834	2.442		
		PEU4	0.890	3.290		
		PEU5	0.851	2.542		
		PEU6	0.810	2.090		
	PU	PU1	0.875	3.227	0.753	0.948
		PU2	0.905	4.162		
		PU3	0.886	3.548		
		PU4	0.904	3.941		
		PU5	0.892	3.568		
		PU6	0.733	1.619		
Career planning (CP)		CP1	0.862	2.716	0.793	0.951
		CP2	0.904	3.639		
		CP3	0.884	3.048		
		CP4	0.905	4.157		
		CP5	0.898	3.947		
Graduate Perceived Employability (GPE)	PPR	PPR1	0.889	2.806	0.793	0.939
		PPR2	0.903	3.425		
		PPR3	0.887	2.714		
		PPR4	0.883	3.268		
	PSA	PSA5	0.810	3.113	0.700	0.942
		PSA6	0.823	2.538		
		PSA7	0.842	2.825		
		PSA8	0.850	2.739		
		PSA9	0.871	3.096		
		PSA10	0.800	2.299		
		PSA11	0.858	2.875		
	CC	CI12	0.802	2.985	0.626	0.930
		CI13	0.853	3.358		
		CI14	0.851	3.529		
		CI15	0.859	3.736		
		RC16	0.826	2.605		
		RC17	0.754	2.138		
		RC18	0.709	2.443		
		RC19	0.651	2.301		
	CEA	CEA20	0.829	3.015	0.716	0.953
		CEA21	0.853	3.545		
		CEA22	0.853	3.258		
		CEA23	0.842	2.770		
		CEA24	0.865	3.097		
		CEA25	0.860	3.129		
		CEA26	0.838	3.479		
		CEA27	0.831	2.770		

Notes: 1. PEU: perceived ease of use; PU: perceived usefulness. 2. PPR: perceived program relevance; PSA: program and self-awareness; CC: Career commitment; IC: Identification with commitment; RC: reconsideration of commitment; CEA: career exploration and awareness.

Table 3 below demonstrates acceptable discriminant validity using the Heterotrait-Monotrait Ratio (HTMT). In this study, PPR, PSA, CC, and CEA form the first-order structure of GPE. As a result, GPE demonstrates acceptable HTMT values when correlated with its first-order dimensions: PPR (HTMT=0.929), PSA (HTMT=0.982), CC (HTMT = 0.949), and CEA (HTMT = 0.972). These elevated HTMT values are theoretically permissible and do not inherently contradict the fundamental assumption that the underlying variables ought to be mutually distinct (Henseler et al., 2015). Moreover, the HTMT value between PSA and PPR (0.909) slightly exceeds the 0.90 threshold proposed by Henseler et al. (2015), yet remains within the relaxed tolerance range recommended by Hair et al. (2021) (Henseler et al., 2015; Joseph F. Hair et al., 2021). To ensure discriminant validity, it is advised that the average variance extracted (AVE) should exceed 0.50 and surpass the square correlation coefficient. All AVE values for variables involved in this study exceed 0.5.

Table 3. Discriminant Validity - Heterotrait-Monotrait Ratio (HTMT)

	1	2	3	4	5	6	7	8
1. Career commitment	-							
2. Career exploration and awareness	0.821	-						
3. Career planning	0.573	0.668	-					
4. Graduate perceived employability	0.949	0.972	0.714	-				
5. Perceived ease of use	0.484	0.530	0.598	0.570	-			
6. Perceived program relevance	0.760	0.816	0.707	0.929	0.538	-		
7. Program and self-awareness	0.817	0.879	0.744	0.982	0.585	0.909	-	
8. Perceived usefulness	0.530	0.593	0.686	0.635	0.686	0.608	0.655	-

Structural Model

Figure 2 presents the structural modelling results. The structural model exhibits no issues with collinearity, as evidenced by all Variance Inflation Factor (VIF) values remaining well within acceptable limits, specifically below the conservative threshold of 5 (Joseph F. Hair et al., 2021). Where covariance is not an issue, R^2 measures the variance explained. The R^2 value for GPE is 0.545, indicating a moderate level of explanation and suggesting the model is a relatively strong predictor of GPE. The R^2 values for PU and CP were 0.407 and 0.451 respectively. The f^2 effect sizes in this study were small. As all Q^2 values surpassed zero, the PLS path model confirms its predictive relevance for the constructs under consideration.

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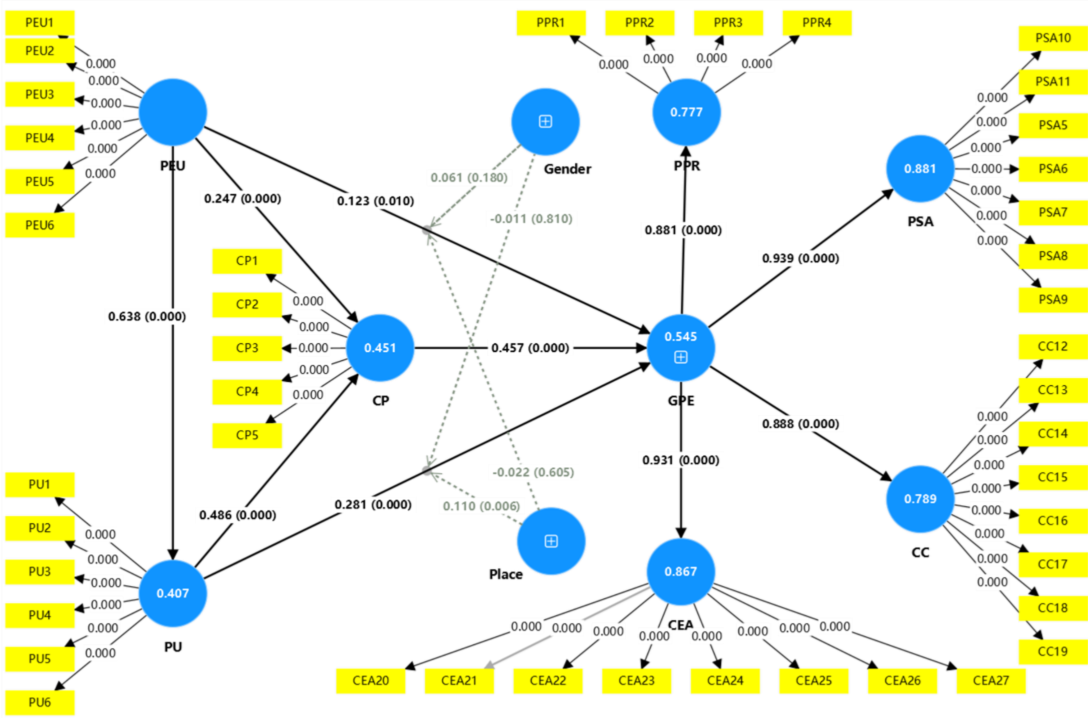

Figure 2: Structural Model Results

Source: author's own notes.

To test the hypotheses, the statistical significance of the variables was examined. As detailed in Table 4, the findings reveal a series of significant and positive relationships: PEU influences GPE (β = 0.123, P = 0.010), PU influences GPE (β = 0.281, P < 0.001), and PEU influences PU (β = 0.638, P < 0.001). Furthermore, PEU exerts a significant positive impact on CP (β = 0.247, P < 0.001), as does PU on CP (β = 0.486, P < 0.001). Finally, CP significantly and positively impacts GPE (β = 0.457, P < 0.001). The mediating role of CP was also confirmed. Thus, all proposed hypotheses for this study were supported.

Table 4: Hypotheses Testing

Hypothesis	β	T	P-Value	Test	R^2	f^2	Q^2	VIF
H_1: PEU >GPE	0.123	2.581	0.010	Supported	0.545	0.013	0.304	2.464
H_2: PU >GPE	0.281	5.291	0.000	Supported		0.060		2.897
H_3: PEU > PU	0.638	19.654	0.000	Supported	0.407	0.687	0.302	1.000
H_4: PEU >CP	0.247	5.032	0.000	Supported	0.451	0.066	0.354	1.687
H_5: PU >CP	0.486	10.551	0.000	Supported		0.255		1.687
H_6: CP >GPE	0.457	9.981	0.000	Supported		0.242		1.896
H_7: PEU >CP >GPE	0.113	4.594	0.000	Supported				
H_8: PU >CP >GPE	0.222	7.543	0.000	Supported				

Source: author's own notes.

Dicussion and Conclusion

Graduates' PEU of AI is positively correlated with their perceived employability (H1). While direct research on the relationship between PEU and GPE specifically concerning AI is currently scarce, the existing literature provides valuable insights into their potential connection. For instance, AI literacy exhibits a significant correlation with university students perceived employability (Wut et al., 2025). Simultaneously, empirical research drawing from the Technology Acceptance Model (TAM) highlights PEU as a crucial determinant of students' AI tool adoption and their usage attitudes (Karan & Chakma, 2025). Further evidence indicates that the effective use of AI can significantly enhance learners' employability by fostering skill development (Lewton & Haddad, 2024; Shi & Wang, 2025). The findings from these studies jointly suggest a plausible mechanism for this relationship, and the present investigation also offers empirical validation for this association. Specifically, when graduates perceive AI tools as more user-friendly, they exhibit greater willingness for sustained use, thereby enhancing relevant skills and competencies. This, in turn, strengthens GPE. Nowadays, AI is extensively deployed across diverse facets of human life, including education, commerce, healthcare, finance, and transportation, thereby elevating our perceived usefulness of AI (Zeng et al., 2021; Кубатко et al., 2024). This precisely confirms PU of AI is pivotal in boosting GPE (H2). The findings of this study are highly consistent with those from a study conducted among university students in Hong Kong (Wut et al., 2025). From the graduate's perspective, AI demonstrates cost-effective and readily available advantages in the career decision-making process, making it a vital tool for supporting graduates in their employment choices (Huang, 2025). Meanwhile, higher education institutions in China are increasingly adopting AI to enhance the efficiency and precision of career guidance and personalised services (Shi & Wang, 2025; Xiaoqing & Noordin, 2024). This development is transformative, optimizing traditional employment guidance and fostering a more efficient, flexible, and responsive paradigm for career development services. It thereby creates enhanced opportunities for graduates to improve their competitiveness in the complex and constantly shifting labor market (Huang, 2025; Shi & Wang, 2025).

The findings of this study indicate that PEU and PU indirectly influence GPE through CP. This conclusion is, to some extent, corroborated by existing research. Previous scholars have pointed out that a technology's ease of use can enhance users' willingness to adopt it, while perceived usefulness significantly strengthens individuals' trust and reliance on tools for career development, thereby indirectly boosting their employment confidence (Zhang et al., 2023; Zhao et al., 2025). However, prior research frequently establishes a direct relationship between technology acceptance and learning or performance outcomes, yet a comprehensive examination of career planning's bridging function within this process remains scarce (Hsu & Lin, 2024; Lin & Yu, 2023; Teo, 2011). Such direct assumptions fail to acknowledge that graduates must still actively engage in planning, reflection, and action when leveraging AI tools/platforms to translate technological advantages into tangible employment competitiveness. This is particularly salient within the Chinese higher education context, where CP is often hampered by information asymmetry and inadequate guidance resources, a reality scarcely examined in the existing literature (Xiaoqing & Noordin, 2024). Consequently, a key innovation of this study is its elucidation of the critical mechanism through which CP mediates between technological cognition and employability. It underscores that AI technology can genuinely enhance employment competitiveness only when strategically embedded within students' career development trajectories. This finding not only aligns with the SCCT emphasis on the interplay between individual cognition and career outcomes but also resonates with the dynamic connections revealed by the SOR framework between external stimuli (AI technology), the organismic state (PEU, PU and CP), and the response (GPE and employment outcomes). As a result, this research provides practical insights for universities developing AI-driven career guidance services.

Furthermore, gender did not significantly moderate the effect pathways from PEU to GPE and from PU to GPE, indicating that the impact of AI perceptions on employability remains consistent across different gender groups. This finding supports the generalisability of AI interventions across different gender groups, indicating that the role of technological literacy in enhancing employability remains stable across gender dimensions (González-Anleo et al., 2024). Whereas place of birth exhibited a significant moderating effect on the PU→GPE pathway, suggesting that differences in developmental environments may influence the extent to which graduates translate their perceptions of AI's practicality into employability. This finding once again confirms that the environment in which one grows up or regional background influences the efficiency with which individuals translate their perception of the usefulness of AI into employability (Tao & Hao, 2023). As noted by Paccoud et al. (2021), disparities exist among students from different regions in terms of access to educational resources, exposure to AI technologies, and digital literacy (Paccoud et al., 2021). These variations consequently affect their capacity to translate the potential value of AI tools into tangible professional competencies. Therefore, when promoting AI-enabled career planning, higher education institutions should account for regional contextual differences and provide more targeted support in technical training and career guidance. This approach aims to mitigate the impact of disparities in digital literacy and resource availability.

This study reveals that AI influences graduate employment outcomes through an “indirect” and “hierarchical” pathway. Unlike prior research that primarily linked technology acceptance directly to learning performance or employment outcomes, this study finds that AI’s impact does not directly target distant employment outcomes (Al-Adwan et al., 2023; An et al., 2023). Rather, its impact is channeled through a sequence of layers, encompassing behavioral beliefs, career planning, and perceived employability. By emphasizing AI’s function as a macro-stimulus driving individual behavior and illustrating that response outcomes are transformed via multiple psychological and behavioral mechanisms before culminating in distant employment performance, this conclusion significantly enriches stimulus-response logic of SOR framework (Pan et al., 2024). Simultaneously, the present research broadens the applicability of SCCT by illustrating that within higher education environments shaped by AI intervention, individual cognitive mechanisms such as self-efficacy and outcome expectancy are not isolated phenomena (Wang et al., 2022). Instead, they are embedded within a chain of mediating factors that combine technology use with career development. Therefore, the framework constructed in this study not only rectifies the linear assumption of “technology → outcome” but also offers a new interpretative pathway for future research investigating how technological interventions influence distant employment outcomes via meso-level career development processes.

This study uncovered the unique operational mechanisms of AI within higher education career development, confirming that PEU and PU influence GPE through CP. This study not only deepens understanding of SCCT and SOR theories within technological contexts but also offers practical insights for higher education institutions on effectively leveraging AI to enhance career guidance and service models, thereby advancing the digital transformation of career

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planning in higher education in Gansu Province, China. Nevertheless, several limitations persist that warrant further exploration in future research. Primary data for this study was collected from a finance and economics university located in Gansu Province. Consequently, the sample exhibits a relatively homogeneous regional and disciplinary profile, which could constrain the generalizability of the study's conclusions. The research design is based on a cross-sectional survey, thus unable to reveal dynamic changes or causal relationships between variables. The mediating mechanisms included in the model are likewise somewhat constrained, failing to capture additional psychological and behavioral factors that might shape graduates' perceptions of employment. Furthermore, this study implicitly assumes a high level of acceptance towards AI tools/platforms among university graduates during career planning. In real-world contexts, yet graduates exhibit significant disparities in digital literacy, AI usage habits, and levels of technology acceptance. These differences may affect the model's robustness. model. Despite certain limitations in sample scope and research design, the findings lay a solid foundation for future investigations into the relationship between AI and employability among students within broader higher education contexts. It is worth noting that the contribution of this research lies not in constructing a context-dependent "Chinese model", but rather in revealing, from a practical perspective, the general mechanism by which artificial intelligence, when embedded within career planning practices, influences graduates' perceived employability through behavioural beliefs and career planning pathways. Therefore, the findings possess a degree of transferability and can provide empirical evidence for higher education institutions in different countries and regions as they advance AI-enabled career preparation.

It is worth emphasising that, whilst this study confirms the positive role of AI in career planning within higher education, it remains necessary to maintain a cautious and critical reflection on the application of technology. AI systems are not value-neutral, as their operational logic heavily relies on existing data, algorithmic design, and institutional assumptions (Chen, 2023). This may inadvertently replicate or amplify structural inequalities within the labour market, such as implicit biases towards specific institutional backgrounds, disciplinary fields, or social capital (Yulianti, 2025). When graduates become overly reliant on AI recommendations during career planning, their professional choices may become "preset" by algorithmic logic, exhibiting tendencies towards "automated bias" (Alon-Barkat & Busuioc, 2023). The result is a potential restriction on individuals' capacity for autonomous reflection and diverse exploration. Meanwhile, as reviewed by Westman et al. (2021), career advice provided by AI often relies on quantifiable metrics and historical trends, struggling to fully capture the highly contextual, dynamic, and emotional factors inherent in individual career development (Westman et al., 2021). This may diminish the essential function of career planning as a process of self-construction and meaning making. Higher education institutions promoting AI-integrated career guidance should acknowledge significant disparities among graduates in digital literacy, AI usage experience, and technological trust, as AI does not automatically translate into universally effective career empowerment tools. Without necessary guidance and support, technology may instead exacerbate the "digital divide", placing resource-constrained students at new disadvantages in career planning. Therefore, the AI effects revealed in this study should be understood as conditional outcomes embedded within institutional and practical contexts, rather than a universally applicable technological determinism conclusion. It must also be acknowledged that AI should function as an assistive decision-support tool in the information age, not as a substitute decision-maker. Strengthening students' critical usage capabilities, self-reflective awareness, and career self-determination through institutional design remains the ultimate goal of career development education. It is only when technological support and human judgement complement each other that AI can genuinely serve graduates' long-term and sustainable career development.

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Ethics Statement:	This study was conducted in accordance with ethical research standards. All procedures involving human participants were reviewed and approved by the Universiti Malaya Research Ethics Committee, approval number UM.TNC(P&I)-UMREC_5153. Informed consent was obtained from all participants prior to data collection. Participation was voluntary, and respondents were assured of confidentiality and anonymity. The data collected were used solely for academic purposes.
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