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Interplay among behavioural beliefs, AI self-efficacy, and perceived employability in AI-assisted career preparation: Findings from PLS-SEM and NCA

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ABSTRACT

This study contributes to the existing literature by extending research on AI-enabled career preparation and perceived employability through an integrated mediation framework involving behavioural beliefs, AI self-efficacy, and perceived employability. This study uses a new estimation methodology by combining PLS-SEM and Necessary Condition Analysis (NCA) to examine both sufficiency and necessity relationships. This study introduces a new analytical framework that integrates sufficiency-based and necessity-based reasoning to explain how AI-related behavioural beliefs contribute to graduates' perceived employability. This study is one of the few to directly break down AI self-efficacy into dimensions such as assisting ability, human-computer anthropomorphic interaction, AI usage comfort, and technical skills, and to examine the relationship between these dimensions and graduates' perceived employability from the perspectives of mediation mechanisms and necessary conditions. The paper provides the first logical analysis of the relationship between graduates' AI-related behavioural beliefs, various dimensions of AI self-efficacy, and perceived employability from the two logical perspectives of sufficiency and necessity. The paper's primary contribution is the finding that behavioural beliefs positively influence perceived employability through the partial mediating role of AI self-efficacy, while AI self-efficacy and its dimensions are necessary conditions for higher perceived employability. This study demonstrates that sufficiency logic and necessity logic are complementary in revealing the relationship between behavioural beliefs, various dimensions of AI self-efficacy, and graduates' perceived employability, and provides empirical evidence for universities to effectively integrate AI tools into career preparation and career development practices.

Contribution/ Originality: This study integrates sufficiency and necessity logic to examine the relationship between behavioral beliefs, AI self-efficacy, and perceived employability. It not only elucidates the combination of factors influencing outcomes but also identifies the critical conditions necessary for achieving a high level of perceived employability in an AI-assisted environment.

1. INTRODUCTION

As society evolves and the labor market transforms, employability requirements for graduates have become increasingly multifaceted. Beyond professional knowledge and basic skills, individuals need self-awareness and career decision-making abilities in career preparation, namely, an understanding of their own strengths, interests, and career inclinations [1]. These psychological factors play a central role in career preparation and development [2], but

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existing research mainly focuses on behavioral outcomes or technology acceptance, failing to systematically reveal how individuals internalize technological information into behavioral beliefs and self-efficacy, thereby developing stronger perceived employability.

Meanwhile, the application of artificial intelligence (AI) technology in career planning provides new tools for understanding individual cognitive processes. For example, through AI mock interviews, personalized feedback, and intelligent career recommendation systems, AI can assist individuals in identifying their abilities and career preferences, thereby supporting more effective career exploration and decision-making [3-6]. These systems utilize algorithms and natural language processing techniques to generate personalized career competency feedback, enabling graduates to perceive their strengths and potential development directions more accurately, thereby cognitively optimizing career choices and planning [7, 8]. However, existing research on the relationships among individual behavioral beliefs, self-efficacy in human-AI collaborative scenarios, and career confidence remains insufficient, particularly lacking a comprehensive analysis of the sufficiency of these psychological conditions and their threshold effects.

Previous research has typically identified key factors by examining statistically significant determinants from a sufficiency perspective and establishing positive and negative correlations [9]. Unlike traditional path analysis, this paper employs a combined approach using PLS-SEM and Necessary Condition Analysis (NCA) to understand key factors from a dual perspective. As proposed by Dul [10], certain necessary conditions or breakthroughs are required to achieve specific outcomes, and without these conditions, the outcomes cannot occur [10]. Therefore, this study uses PLS-SEM to examine the sufficiency paths from behavioral beliefs and AI self-efficacy to perceived employability, while employing NCA to assess the necessity of key psychological conditions. This reveals that, in a technology-supported career planning environment, students' behavioral beliefs and self-efficacy regarding AI technology may constitute cognitive impairments that prevent high perceived employability. This complementary perspective not only enhances the explanatory power of the theory but also helps clarify the potential limitations of educational technology in career preparation.

The theoretical framework of this study is based on Decision Intelligence Theory (DIT), which focuses on career preparation and employment confidence in human-AI collaborative settings. The study begins with behavioral beliefs and examines how they may affect perceived employability through AI self-efficacy. It combines PLS-SEM and NCA to identify the roles of key psychological conditions and potential cognitive barriers from both sufficiency and necessity perspectives. In a technology-supported career-planning environment, this research not only expands our understanding of the psychological mechanisms underlying graduate career readiness but also provides new theoretical and methodological perspectives for educational psychology to explore analytical methods for cognitive and behavioral interactions in technology-enhanced learning environments.

2. LITERATURE REVIEW

2.1. Decision Intelligence Theory

With the rapid development of AI technology and the acceleration of digital transformation in higher education, traditional decision-making models are undergoing a paradigm shift [11]. Decision Intelligence Theory (DIT), as an emerging theoretical framework, integrates artificial intelligence (AI), data science, and classical decision theory to offer a new perspective on understanding individual decision-making behaviour in complex situations [11, 12]. DIT builds upon the foundational principles of classical decision science [13] and the economic rationality model [14] while also incorporating the theoretical assumptions of the technology acceptance model (TAM) regarding individual technology adoption behaviour [15]. As shown in Figure 1, it emphasises how individuals form cognitive structures for intelligent decision-making processes through human–computer collaboration within data-driven environments supported by computational models. Sai-Ke, et al. [16] further classified the evolution of decision-making into three stages: empirical, computable, and intelligent. They pointed out that the "intelligent decision-making" stage

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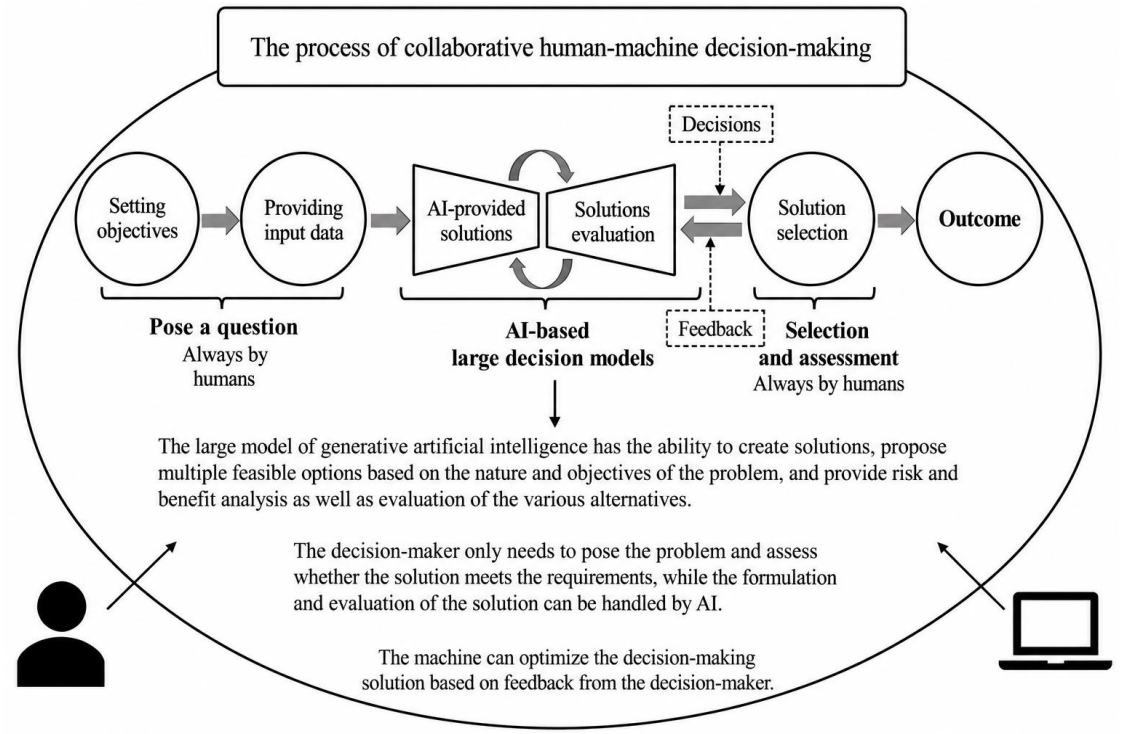
emphasises the enhancement of decision-making foresight, adaptability, and individual perceptual efficiency through the in-depth embedding of AI systems [16]. The intelligent stage emphasises the use of AI systems to assist individuals in developing more systematic cognitive and decision-making patterns.



Source: This diagram is adapted from Combining Human and Artificial Intelligence: Hybrid Problem-Solving in Organizations [17] and Paradigm Shift in Decision-making in the Era of Large Language Models [16].

Figure 1. Human-computer decision-making.

DIT argues that an individual's decision-making ability does not stem solely from internal rational reasoning or accumulated experience, but rather results from dynamic generation and evolution within the interactive process of the "human-technology-environment" system [18]. In the context of deepening digital transformation, technological systems no longer exist merely as information tools, but are deeply embedded in the decision-making process, reconstructing information acquisition methods, cognitive processing paths, and action-selection structures [19]. Therefore, the formation of decision-making ability no longer depends entirely on an individual's cognitive resources, but is built upon the collaborative interaction between the individual and the technological environment. The improvement of individual decision-making quality largely depends on the degree to which they effectively embed themselves in and utilize the technological environment.

Existing research indicates that an individual's decision-making performance is constrained by their information-processing capabilities, which, in turn, significantly depend on the level of support provided by the external technological environment [20]. AI systems, by integrating multisource data, constructing scenario simulations, and providing risk-prediction mechanisms, can effectively reduce decision-making complexity, expand an individual's cognitive boundaries, and enable them to make more forward-looking and rational career judgments in highly uncertain employment situations. For example, AI mock interviews, through the intelligent matching of job requirements, behavioral performance, and feedback mechanisms, not only optimize information presentation but also enhance an individual's clarity in understanding the match between their own abilities and market demands [6]. In this sense, technological support not only has an "instrumental" function but also constitutes a structural prerequisite for the generation of decision-making ability [21]. That is, given the relative scarcity of technological support, the decisions people make about their careers are often constrained by information asymmetry and limited cognitive

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resources, while, given the deep embedding of intelligent technology, an individual's decision-making ability is presented as the product of the interaction between cognitive ability and the functions of the technological system.

At present, some universities in China have gradually explored the introduction of big data and AI technologies into the postgraduate employment service system, promoting the transformation of the career decision-making model from traditional information collection and experience-based judgment to an intelligent decision-making model characterized by algorithmic support and data-driven approaches. For instance, the AI simulation interview platform developed by Renmin University of China provides dynamic and personalized decision support for graduates through an intelligent assessment and feedback mechanism [6]. The digital and intelligent environment not only changes the way graduates obtain career information but also reshapes their career exploration paths and action strategies. Against this backdrop, AI self-efficacy is reflected not only in an individual's subjective confidence in their ability to use technology but also becomes a key mechanism through which individuals embed themselves in the digital decision-making environment and achieve a leap in their capabilities [22]. In other words, the AI technology environment should not be regarded as an external or secondary variable, but rather as a key condition determining the upper limit of decision-making capabilities. An individual's adaptability to the technological environment directly affects their ability to develop career behavioral cognition in a digital employment context.

2.2. Graduates' Perceived Employability

Graduates' perceived employability (GPE), or graduates' subjective perceptions of their employability, concerns not only graduates' evaluations of their personal knowledge, skills, experience, and attributes, but also their confidence that they will be able to secure the job of their dreams [23, 24]. Empirical evidence indicates that career planning education in higher education is effective in improving graduates' perceived employability [25], while greater perceived employability is associated with more positive employment outcomes [26]. Individuals' perceived employability is closely related to their psychological state, self-efficacy, and future expectations, and is also influenced by the combination of their educational background, social resources, and external employment environment.

The rapid development of AI, big data, and digital employment platforms has reshaped the way higher education is conducted, including career planning education. Previous research has shown that AI mock interviews, intelligent career recommendation systems, and online career development platforms can effectively integrate multi-source information, provide contextualized feedback, and simulate real-world career decision-making scenarios, thereby enhancing graduates' awareness of their career abilities and decision-making capabilities [6]. In the digital employment environment, graduates not only need self-awareness and career confidence but also need to develop adaptability to the technological environment to fully utilize AI tools for career exploration and planning [27]. Empirical research further demonstrates that the development of the internet and AI can enhance graduates' perceptions of the external employment environment, making them more proactive and confident in decision-making when facing uncertain and complex situations [28]. Immersive career experiences and virtual simulation assessments, among other technological means, help graduates practice decision-making behaviors in a safe and controlled environment, thereby accumulating experience and improving self-efficacy [29]. It can be said that the technological environment plays a structural and contextual supporting role in this process, making graduates' perceived employability a comprehensive reflection of cognitive abilities, experience accumulation, and technological synergy.

According to research by Bennett, et al. [30], graduates' perceived employability can be understood through four dimensions: (i) self-awareness and career-related planning; (ii) career identity and commitment; (iii) the perceived relevance of career planning; and (iv) career exploration and awareness [30]. In the digital and intelligent employment environment, these dimensions increasingly rely on the cognitive and structural support provided by the technological environment. Therefore, this study is based on the premise that the technological environment is key to enhancing graduates' career cognition and decision-making abilities.

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2.3. Behavioural Beliefs

Behavioural beliefs (BBS) refer to individuals' perceptions of the likely outcomes of a behaviour, which shape their attitudes towards that behaviour and, in turn, influence their behavioural intentions and actual performance [31]. As the core constructs of the Technology Acceptance Model (TAM), behavioural beliefs are mainly represented by users' perceived usefulness (PU) and perceived ease of use (PEU) of technology. Perceived usefulness (PU) refers to the degree to which an individual believes that using a particular technology will enhance their task performance, while perceived ease of use (PEU) refers to the degree to which an individual believes that using a particular technology would require minimal effort to learn and operate [32]. As core behavioural belief variables in the TAM, PU and PEU not only predict users' willingness and behaviour regarding technology use but also constitute antecedents of how technology influences individual cognitive and competency development [31].

In the context of AI, PU reflects graduates' assessment of the practical value of AI tools, such as AI mock interviews and AI resume optimization, in their career preparation process, while PEU reflects their subjective experience with these tools. These behavioral beliefs not only predict graduates' trust in and willingness to use AI technology but also influence whether they incorporate these tools into their career planning and job-seeking strategies [33, 34]. For example, perceived usefulness and perceived ease of use have been found to significantly predict students' dependence on and continued use of AI career platforms, thereby indirectly affecting learning outcomes and career decision-making behavior [33].

Furthermore, BBS not only predicts technology usage behaviour but can also internalise an individual's experience with technology into behavioural cognition. On the one hand, graduates with high PEU and PU are more likely to proactively try and continuously use AI technology, thereby gaining a positive cycle of skill improvement and enhanced feedback [35]. On the other hand, this proactive practice and continuous training, along with positive feedback from AI, are internalised into self-evaluation of personal abilities, consistent with the formation mechanism of GPE. However, most studies do not adequately explore the mechanism by which BBS are internalised into GPE. In actual educational practice, although most studies focus on graduates' PEU and PU regarding AI tools that assist job seeking, there is a lack of practical research on how BBS are internalised into graduates' employment confidence through their experience using technology. For example, existing literature overlooks the influence of individual differences, such as graduates' technological literacy, career goals, learning motivation, and levels of self-efficacy [36]. This means that PU and PEU are not universally applicable to all individuals, and their influence may vary significantly depending on individual traits and environmental conditions. Based on this, this study proposes the following hypotheses to further verify this mechanism in relatively underdeveloped regions with limited technology adoption.

H_1: In AI-embedded career readiness scenarios, graduates' behavioral beliefs about AI (perceived usefulness and perceived ease of use) positively influence their perceived employability.

2.4. AI Self-Efficacy

AI self-efficacy (AISE) refers to an individual's subjective judgment of their own abilities when using AI technologies for task completion, problem-solving, and decision support [37]. Unlike traditional computer self-efficacy, it encompasses not only the ability to operate AI technologies but also an individual's confidence, adaptability, and emotional engagement in interactions with intelligent systems, such as anthropomorphic interaction and comfort [37]. Especially in the context of the widespread application of generative AI, this concept has gradually become a key psychological indicator for measuring an individual's "embedded decision-making ability."

Theoretically, AISE is rooted in Bandura [38] social cognitive theory of self-efficacy, which is considered a core psychological mechanism influencing behavioral choices, effort levels, and persistence [39]. It has gradually expanded in the context of rapid technological evolution, encompassing computer self-efficacy, technological self-efficacy, digital self-efficacy, and other related branches [40-42]. However, in the contemporary context, where AI is

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highly embedded in career decision-making processes, traditional technological self-efficacy is insufficient to explain how individuals utilize intelligent systems for career exploration and decision optimization. AISE thus becomes a key variable connecting the "technological environment" and "career competence construction" [35]. This aligns perfectly with the focus of decision intelligence theory (DIT). Whether graduates can effectively embed themselves in intelligent technological environments and utilize technological resources to expand their cognitive boundaries depends on their level of AI self-efficacy. In other words, AISE is not only a psychological extension of technology acceptance but also a necessary condition for the generation and enhancement of decision-making ability. This logic implies that AI self-efficacy may constitute a "threshold variable" for achieving a high level of perceived employability in AI-embedded career decision-making situations [43]. That means that if individuals lack basic confidence and interaction skills with AI, even if the technological system itself possesses high functionality, its promoting effect on perceived employability will be difficult to fully realize. Based on this, this study proposes the following hypotheses.

H_3: In AI-embedded career readiness scenarios, the higher a graduate's AI self-efficacy, the higher their perceived employability.

H_5: In AI-supported career readiness scenarios, graduates can effectively utilize AI tools to achieve a high level of perceived employability, which depends on graduates possessing a certain level of AI self-efficacy.

While previous research has shown that BBS (PU and PEU) can promote the adoption of AI tools [44], existing literature generally treats them as variables that directly predict willingness to use, with less exploration of how they translate into perceived career competence through individual psychological mechanisms. Indeed, merely perceiving technology as "useful" is insufficient to guarantee competence enhancement [45]. If individuals lack confidence in their own operational and application abilities, technological advantages may not translate into effective career actions. This implies that a key psychological mediating mechanism may exist between behavioral beliefs and career outcomes, and AISE is the core manifestation of this mechanism. According to self-efficacy theory, individuals form a belief about their ability to successfully use a certain tool to achieve a specific goal through repeated mastery experiences and positive feedback [35]. In the context of digital career readiness, this belief does not refer to general competence but specifically to whether an individual has the ability to use AI tools effectively to support career decision-making and development tasks. Existing research indicates that perceived employability is essentially a subjective construct of competence beliefs, and its formation depends on an individual's successful experiences in specific occupational tasks and situations [23]. Therefore, in the context of AI embedded in career exploration and decision-making, PU and PEU may first enhance individuals' confidence in their ability to use AI technologies for career exploration and decision support. This context-specific belief in effectiveness is further transformed into a higher-level assessment of one's own employability through continuous practice and feedback loops [46]. However, this psychological transformation mechanism has not yet been systematically verified in artificial intelligence-driven career preparation scenarios. Based on this, this study proposes the following hypotheses to address the insufficient attention given to psychological transformation mechanisms in existing research.

H_2: Graduates' behavioral beliefs about AI (perceived usefulness and perceived ease of use) will positively influence their AI self-efficacy in AI-embedded career readiness contexts.

H_4: In career readiness scenarios infused with AI, graduates' AI self-efficacy has a positive association with their perceived employability (GPE).

Figure 2 presents the theoretical framework of this study, revealing the dual-path interaction mechanism among behavioral beliefs (BBS), AI self-efficacy (AISE), and perceived employability (GPE) in the context of AI-assisted career preparation. In this framework, graduates' behavioral beliefs about artificial intelligence tools (perceived usefulness [PU] and perceived ease of use [PEU]) not only directly enhance their perception of employability but also indirectly influence perceived employability by improving their artificial intelligence self-efficacy, thus forming a complete chain of mediated transmission paths. To control for potential confounding factors, this study included

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gender and place of birth as control variables in the model to eliminate the influence of these demographic characteristics on perceived employability.

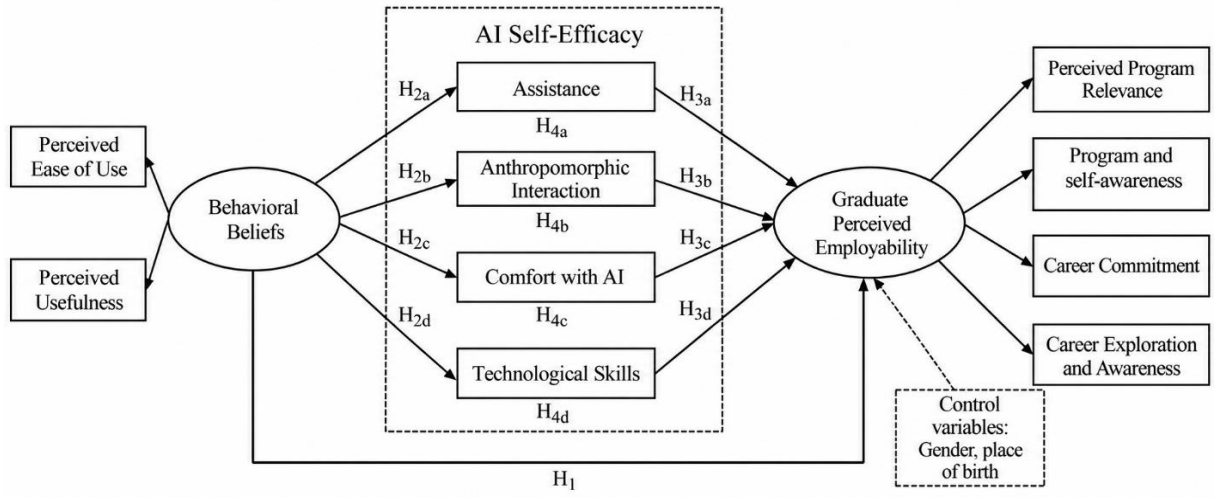

Figure 2. The conceptual research framework.

3. METHODOLOGY

3.1. Procedure and Participants

This study employed a quantitative questionnaire survey method, collecting data from a finance-related university in Northwest China, namely Lanzhou University of Finance and Economics, using convenience sampling between October 2024 and September 2025. It is worth noting that colleges and universities in Gansu Province had not systematically integrated artificial intelligence technology into career planning and employment guidance services before this study. As a pilot institution in the region and the first to introduce artificial intelligence tools, this university provides a representative technical context for examining individual psychological mechanisms and the process of ability construction in the context of artificial intelligence-embedded career preparation. Against this backdrop, the university provided students with a series of artificial intelligence tools for career preparation, including AI resume optimization, AI mock interviews, and AI career matching. Students could interact with AI systems during real career preparation tasks. Therefore, this study did not examine students' general attitudes toward technology at an abstract level, but rather explored the structural relationships among their behavioral beliefs, AI self-efficacy, and perceived employability in a real environment where graduates had used AI tools to assist with career preparation for nearly a year. This study selected graduates as the research subjects because they were at the transitional stage of employment and represented a sample group with high situational relevance for studying employability [25]. Furthermore, existing literature has repeatedly pointed out that students majoring in finance and economics often equate their perceived employability with their actual ability to obtain and maintain regular employment [47, 48]. Therefore, in an AI-supported career preparation environment, their perceptions have more concrete real-world relevance. All questionnaires were completed anonymously, and no identifiable personal information was collected. Before formal data collection, this research protocol was approved by the ethics review committee of the corresponding university. All participants read and confirmed the electronic informed consent form before completing the questionnaire. Participants were informed that their participation was completely voluntary and that they could withdraw unconditionally at any stage without any academic or administrative adverse effects. Approximately 810 people participated in this survey, and a total of 770 complete and valid questionnaires were obtained. As shown in Table 1, the sample consisted of 24% male and 76% female, 62% of the participants had experience in social practice or social activities.

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Table 1. The participants of the study.

Group		N	%
Gender	Male	182	23.64
	Female	588	76.36
Year of Study	Senior	770	100
Place of Birth	Rural	262	34.03
	Urban	508	65.97
Social Engagement	Yes	476	61.82
	No	294	38.18
Kinds of Social Engagement	Internships	91	11.82
	Club activities	261	33.90
	Social networking events	23	2.99
	Student affairs	101	13.12
	None	294	38.18
Usage Status of AI	No	0	0
	Yes	770	100
AI Utilization	Rarely	488	63.38
	Sometimes	238	30.91
	Often	13	1.69
	Always	31	4.02
Total		770	100.00

3.2. Measures

All research instruments used in this study were in English. Since the study focused on graduates from Gansu Province, China, the instruments were translated into Chinese with the assistance of a professional translator and subsequently validated for content by three Chinese experts in education. To further ensure content validity and translation accuracy, the instruments were then back-translated with the help of another expert fluent in both Chinese and English. The back-translator did not have access to the original English questionnaire and subsequently compared the back-translated version with the original to confirm consistency. This study received ethical approval from the Research Ethics Committee.

A seven-point Likert scale (1 = Strongly disagree; 4 = Neutral; and 7 = Strongly agree) was used for all measurement scales in the research model described above. All predefined instruments were utilized in this study. The Behavioural Beliefs Scale was adopted from the 12-item scale developed by Davis [32], which provides the final measures of perceived usefulness and perceived ease of use [32, 49]. The AI Self-Efficacy Scale used in this study was adopted from the original scale developed by Wang and Chuang [37], which measures participants' self-efficacy in using AI across four dimensions, with a total of 22 items [37]. The Graduates' Perceived Employability Scale, comprising 27 items and developed by Bennett and Ananthram [50], captures graduates' perceptions of their employability-related strengths and challenges, as well as their views on the alignment between employability and their learning experiences [50]. All scales are self-report instruments.

3.3. Data Analysis

This study used SmartPLS 4.0 and R software for data analysis. First, variance-based structural equation modeling (PLS-SEM) was conducted in SmartPLS 4.0 to test the hypothesized paths and mediation mechanisms. Second, necessary condition analysis (NCA) was performed in R software to determine whether AI self-efficacy constitutes a necessary condition for achieving a higher level of perceived employability in AI-assisted career readiness scenarios. In the sufficiency analysis phase, variance-based structural equation modeling (PLS-SEM) was used to evaluate the measurement and structural models [51]. In evaluating the measurement model, the constructs' internal consistency reliability, convergent validity, and discriminant validity were tested. Subsequently, in the structural model, the hypothesized relationships were evaluated using path coefficients, coefficients of determination (R^2), and effect sizes (f^2), and the significance of the path coefficients was tested using bootstrapping with 5,000

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resamplings [51]. In the necessity analysis phase, Necessary Condition Analysis (NCA) was used to examine whether AI self-efficacy (AISE) constitutes a necessary condition for achieving a higher level of perceived employability (GPE). Unlike PLS-SEM, which focuses on the "sufficient effect" of variables, NCA identifies whether a variable is an indispensable prerequisite for the outcome variable to reach a certain level, thereby revealing potential threshold effects [10]. By calculating the effect size (d) and drawing a ceiling line, this study further examined whether [52] in a context where AI supports career exploration and decision-making, a certain level of AI self-efficacy (AISE) constitutes an indispensable prerequisite for graduates to achieve a high level of perceived employability through AI tools.

4. FINDINGS

4.1. Common Method Bias and Multicollinearity

This study used a cross-sectional research design for data collection. To control for common method variance (CMV) and multicollinearity, the study used several tests, including the variance inflation factor (VIF) test and Harman's one-way test [25]. The results showed that the VIF values for all latent variables were below 5.0, indicating that multicollinearity was not a significant problem [51]. The Harman one-way test results revealed the extraction of nine factors with eigenvalues greater than 1.0, the smallest being 1.153. Together, these factors accounted for 69.515% of the total variance, approximately 70% [53]. Thus, the factor analysis extracted multiple factors with eigenvalues greater than 1.0, and the proportion of variance explained by the first factor was much less than 50%. This suggests that no single factor dominated the main variance and that the nine factors explained approximately 70%, indicating a better structure. Therefore, it can be concluded that there was no threat of CMV in this study.

4.2. The Analysis Results of PLS-SEM

4.2.1. Measurement Model Assessment

Table 2 reports the initial measurement model results before one of the items (AS2), under the assistance dimension of AI self-efficacy as a latent variable, fell below the minimum threshold of 0.40 [51]. It was removed. This study compared the indicator loadings against the recommended threshold of 0.708. All other findings were acceptable in terms of internal consistency reliability and convergent validity.

Table 2. Initial Measurement Model Assessment Results (Before Item Removal).

Construct	Item	Loading	VIF	rho_c	AVE
Behavioural beliefs:					
Perceived usefulness	PU1	0.880	3.227	0.948	0.754
	PU2	0.911	4.162		
	PU3	0.892	3.548		
	PU4	0.907	3.941		
	PU5	0.895	3.568		
	PU6	0.709	1.619		
Perceived ease of use	PEU1	0.831	2.407	0.936	0.708
	PEU2	0.837	2.487		
	PEU3	0.838	2.486		
	PEU4	0.890	3.378		
	PEU5	0.846	2.631		
	PEU6	0.805	2.334		
AI self-efficacy:					
Assistance	AS1	0.681	1.420	0.807	0.385
	AS2	0.391	1.387		
	AS3	0.557	1.500		
	AS4	0.794	1.858		
	AS5	0.655	1.510		
	AS6	0.705	1.545		
	AS7	0.459	1.200		
Anthropomorphic interaction	AI8	0.517	1.346	0.850	0.536
	AI9	0.812	1.994		

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Construct	Item	Loading	VIF	rho_c	AVE
	AI10	0.716	1.646		
	AI11	0.806	1.997		
	AI12	0.769	1.568		
Comfort with AI	CF13	0.828	2.859	0.944	0.738
	CF14	0.856	3.742		
	CF15	0.861	3.783		
	CF16	0.883	4.549		
	CF17	0.887	4.492		
	CF18	0.838	4.567		
Technological skills	TS19	0.865	4.528	0.930	0.768
	TS20	0.878	2.893		
	TS21	0.917	3.682		
	TS22	0.843	2.486		
Graduate perceived employability:					
Perceived program relevance	PPR1	0.889	3.067	0.939	0.793
	PPR2	0.903	3.425		
	PPR3	0.887	2.714		
	PPR4	0.883	3.268		
Program and self-awareness	PSA5	0.810	2.214	0.942	0.700
	PSA6	0.823	2.708		
	PSA7	0.841	2.616		
	PSA8	0.850	2.739		
	PSA9	0.871	3.096		
	PSA10	0.800	2.299		
	PSA11	0.858	2.875		
Career commitment Factor 1: Career identity (identification with commitment) (4 items) Factor 2: Reconsideration of commitment (4 items)	CC12	0.802	2.513	0.930	0.626
	CC13	0.853	3.358		
	CC14	0.851	3.529		
	CC15	0.859	3.736		
	CC16	0.826	2.441		
	CC17	0.754	2.277		
	CC18	0.709	2.329		
	CC19	0.652	2.301		
Career exploration and awareness	CEA20	0.829	2.822	0.953	0.716
	CEA21	0.853	3.856		
	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	2.634		

Table 3 shows the discriminant validity of the Heterotrait-Monotrait Ratio (HTMT).

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

Variables	1	2	3	4	5	6	7	8	9	10	11	12
1	-											
2	0.626	-										
3	0.523	0.554	-									
4	0.702	0.718	0.557	-								
5	0.617	0.658	0.617	0.821	-							
6	0.604	0.664	0.566	0.772	0.676	-						
7	0.686	0.724	0.663	0.949	0.972	0.750	-					
8	0.476	0.483	0.971	0.484	0.530	0.495	0.570	-				
9	0.616	0.660	0.630	0.760	0.816	0.673	0.929	0.538	-			
10	0.621	0.663	0.682	0.817	0.879	0.672	0.982	0.585	0.909	-		
11	0.477	0.524	0.969	0.530	0.593	0.534	0.635	0.686	0.608	0.655	-	
12	0.532	0.640	0.528	0.733	0.626	0.930	0.710	0.467	0.639	0.648	0.494	-

Note: 1. Anthropomorphic interaction; 2. Assistance; 3. Behavioural beliefs; 4. Career commitment; 5. Career exploration and awareness; 6. Comfort with AI; 7. Graduate perceived employability; 8. Perceived ease of use; 9. Perceived program relevance; 10. Program and self-awareness; 11. Perceived usefulness; 12. Technological skills.

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Since PEU and PU are first-order constructs of BBS, and PPR, PSA, CC, and CEA are first-order constructs of GPE, the higher HTMT values between them (HTMT > 0.90) are theoretically justifiable and do not constitute a direct violation of the fundamental assumption that the underlying constructs should be distinct from one another [54]. Additionally, the HTMT value between PSA and PPR is 0.909, which, although high, remains within an acceptable tolerance range [51, 54]. In this study, considering that both are theoretically internal dimensions of perceived employability (GPE), it is reasonable to retain both of them as first-level constructs of GPE. However, since the HTMT value between CF and TS exceeded the proposed threshold of 0.90 (HTMT = 0.930), the two constructs were combined into one construct called "AI Technology Confidence" (ATC). All pairs of constructs, except for the pair mentioned above, exhibited HTMT values well below the empirical threshold of 0.90, and the revised HTMT results are presented in Table 4 to reflect the adjustments made to the construct structure.

Table 4. Discriminant validity of the constructs after combining CF & TS.

Variables	1	2	3	4	5	6	7	8	9	10	11
1											
2	0.626										
3	0.587	0.667									
4	0.523	0.554	0.561								
5	0.702	0.718	0.771	0.557							
6	0.617	0.658	0.669	0.617	0.821						
7	0.686	0.724	0.748	0.663	0.949	0.972					
8	0.476	0.483	0.493	0.971	0.484	0.530	0.570				
9	0.616	0.660	0.672	0.630	0.760	0.816	0.929	0.538			
10	0.621	0.663	0.675	0.682	0.817	0.879	0.982	0.585	0.909		
11	0.477	0.524	0.528	0.969	0.530	0.593	0.635	0.686	0.608	0.655	

Note: 1. Anthropomorphic interaction; 2. Assistance; 3. AI technology confidence; 4. Behavioural beliefs; 5. Career commitment; 6. Career exploration and awareness; 7. Graduate perceived employability; 8. Perceived ease of use; 9. Perceived program relevance; 10. Program and self-awareness; 11. Perceived usefulness.

Based on the above statistical results and theoretical considerations, the two sub-hypotheses within each of the original hypotheses H_2, H_3, and H_4 in this study were combined and adjusted as follows:

The original sub-hypotheses (H_{2c} and H_{2d}) under Hypothesis H_2 were conceptually and statistically integrated into a single hypothesis ($H_{2c'}$):

$H_{2c'}$: There is a significant influence of behavioral beliefs on AI technology confidence among university graduates in Gansu Province, China.

The original sub-hypotheses (H_{3c} and H_{3d}) under Hypothesis H_3 were conceptually and statistically integrated into a single hypothesis ($H_{3c'}$):

$H_{3c'}$: There is a significant influence of AI technology confidence on graduates' perceived employability among university graduates in Gansu Province, China.

The original sub-hypotheses (H_{4c} and H_{4d}) under Hypothesis H_4 were conceptually and statistically integrated into a single hypothesis ($H_{4c'}$):

$H_{4c'}$: There is a significant mediating effect of AI technology confidence on the relationship between behavioral beliefs and graduates' perceived employability among university graduates in Gansu Province, China.

4.2.2. Structural Model Assessment

In the structural model, there was probably no collinearity issue because all VIF figures were well below the threshold value of 5 [51]. If covariance is not an issue, R^2 measures the variance explained. The R^2 value for GPE was 0.676, indicating a moderate level and suggesting that the model is a relatively strong predictor of GPE. The R^2 values for assistance, anthropomorphic interaction, and AI technology confidence were 0.201, 0.204, and 0.282, respectively. f^2 effect values were small in this study, and the Q^2 values were all greater than zero (Q^2 = 0.389),

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suggesting that the PLS pathway model has predictive relevance for the research constructs [51]. Figure 3 illustrates the structural modelling results.

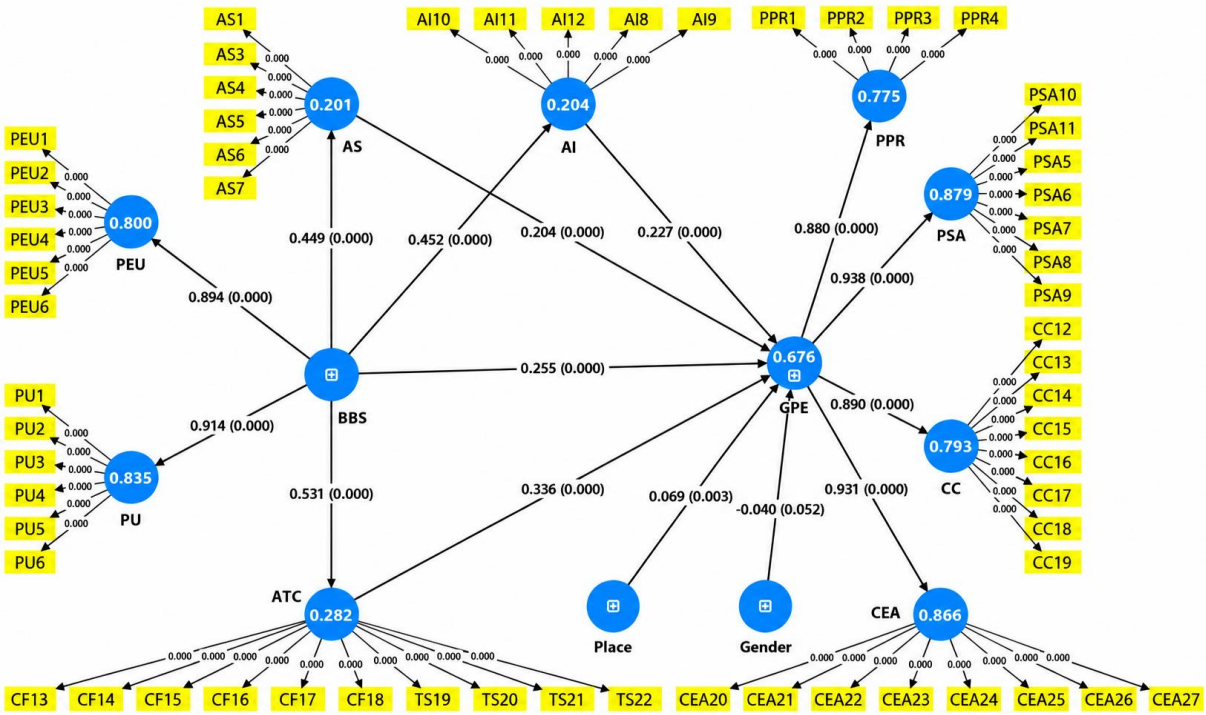

Figure 3. Structural model results.

Table 5. Hypotheses testing.

Hypothesis		Coefficient	p	f^2	Text
H_1: BBS >GPE		0.255	0.000	0.136	Supported
H_2: BBS>AISE					Supported
H_{2a}: BBS >AS		0.449	0.000	0.273	Supported
H_{2b}: BBS >AI		0.452	0.000	0.256	Supported
H_{2c}: BBS >CF	$H_{2c'}$: BBS >ATC	0.531	0.000	0.393	Supported
H_{2d}: BBS >TS					
H_3: AISE >GPE					Supported
H_{3a}: AS >GPE		0.204	0.000	0.074	Supported
H_{3b}: AI >GPE		0.227	0.000	0.094	Supported
H_{3c}: CF >GPE	$H_{3c'}$: ATC >GPE	0.336	0.000	0.184	Supported
H_{3d}: TS >GPE					
H_4: BBS >AISE >GPE					Supported
H_{4a}: BBS >AS >GPE		0.091	0.000		Supported
H_{4b}: BBS >AI >GPE		0.103	0.000		Supported
H_{4c}: BBS >CF >GPE	$H_{4c'}$: BBS >ATC >GPE	0.178	0.000		Supported
H_{4d}: BBS >TS >GPE					

Table 5 shows the results of all hypothesis tests. H1 posits that BBS positively influences GPE. The findings indicate that the relationship is significant, $\beta = 0.255$ ($t = 5.894$, $p < 0.001$). Therefore, H1 was significantly supported. H2 (H2a, H2b, and H2c') examined the effects of graduates' behavioural beliefs about AI tools on feelings of assistive efficacy, anthropomorphic efficacy, and technological confidence in AI, respectively. The results showed that behavioural beliefs had significant effects on the efficacy of AI assistance, anthropomorphic interaction, and AI technology confidence. Therefore, H2 (H2a, H2b, and H2c') was supported. H3 (H3a, H3b, and H3c') predicted a positive relationship between AISE and GPE. GPE was significantly influenced by the efficacy of AI assistance,

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anthropomorphic interaction, and AI technology confidence. Therefore, the results significantly supported H3 (H3a, H3b, and H3c'). H4 (H4a, H4b, and H4c') examined the mediating role of AI self-efficacy in the relationship between BBS and GPE. To test this mediating role, we followed the approach developed by Preacher, et al. [55], which emphasises the use of indirect effects to demonstrate mediation [55]. The indirect effect of BBS on GPE through AISE was significant, and H4 (H4a, H4b, and H4c') was supported.

4.3. The Analysis Results of NCA

To further determine the relationship between AISE and high GPE in the context of AI-assisted career preparation for graduates, this study supplemented the PLS-SEM results with NCA. Specifically, the latent variable scores of AISE and GPE calculated using PLS-SEM were used as inputs for NCA, and R software was used to perform NCA and derive the effect size (d) and p-values for significance testing.

4.3.1. Effect and Significance Analysis

The NCA results (see Table 6) show that AI self-efficacy (AISE) is a necessary condition for graduates to achieve a high level of perceived employability (GPE) in AI-assisted career preparation scenarios. Its effect size is d = 0.204, which, according to Dul [10] criteria, is a moderate effect size and statistically significant ($p < 0.001$) [10]. This result indicates that AISE constitutes an important necessary condition for achieving a higher level of GPE in AI-embedded career preparation environments. Further analysis of the necessary conditions for the four dimensions of AISE revealed that assistance (d = 0.114), anthropomorphic interaction (d = 0.182), comfort with AI (d = 0.171), and technological skills (d = 0.108) all constitute necessary conditions for achieving a higher level of GPE, and all effects reached a statistically significant level (all $p < 0.001$). Based on the effect size criteria, these dimensions generally exhibit small to moderate necessary effects. Among them, anthropomorphic interaction and AI comfort show relatively higher necessary strengths, indicating that human-computer interaction experience and technological adaptability play a crucial threshold role in AI-assisted career preparation.

Table 6. Results of Necessary Condition Analysis (NCA).

Variables	GPE		
	Methods	**Effect size (d)**	**p-value**
AISE-total	CE-FDH	0.204	0.000
	CR-FDH	0.189	0.000
AS	CE-FDH	0.114	0.000
	CR-FDH	0.109	0.000
AI	CE-FDH	0.182	0.000
	CR-FDH	0.168	0.000
CF	CE-FDH	0.171	0.000
	CR-FDH	0.165	0.000
TS	CE-FDH	0.108	0.000
	CR-FDH	0.101	0.000

Note: AISE: AI self-efficacy, including AS, AI, CF and TS. AS: Assistance; AI: Anthropomorphic interaction; CF: Comfort with AI; TS: Technological skills.

The scatter plot of necessity for the total AISE score is shown in Figure 4. As can be observed in the figure, there is a significant blank area in the upper left of the upper envelope (CE-FDH), forming a typical "necessary condition structure." This blank area represents the absence of high-level GPE results under low-level AISE conditions, thus demonstrating the necessity characteristic.

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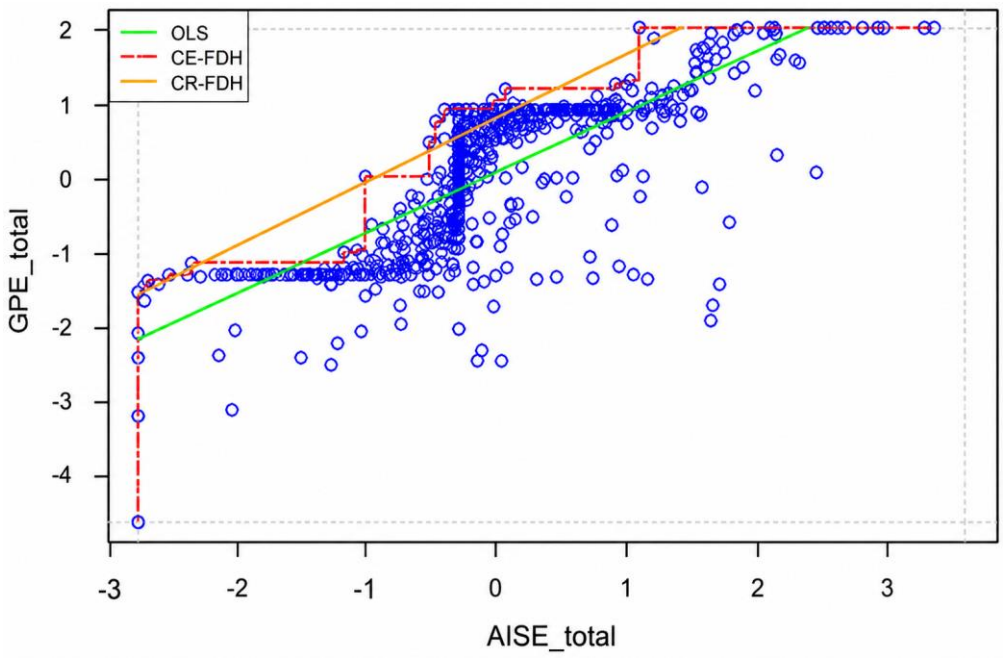

Figure 4. Scatter plot of AI self-efficacy and graduates' perceived employability.

The scatter plots of the necessity of the four dimensions of AISE are shown in Figure 5, respectively. As can be clearly observed in the figures, there is a significant blank area in the upper left of the upper envelope of the CE-FDH, presenting a typical "necessary condition structure." This blank area indicates that high-level GPE results do not appear when each dimension is at a low level, suggesting that these dimensions constitute prerequisites for achieving high-level GPE.

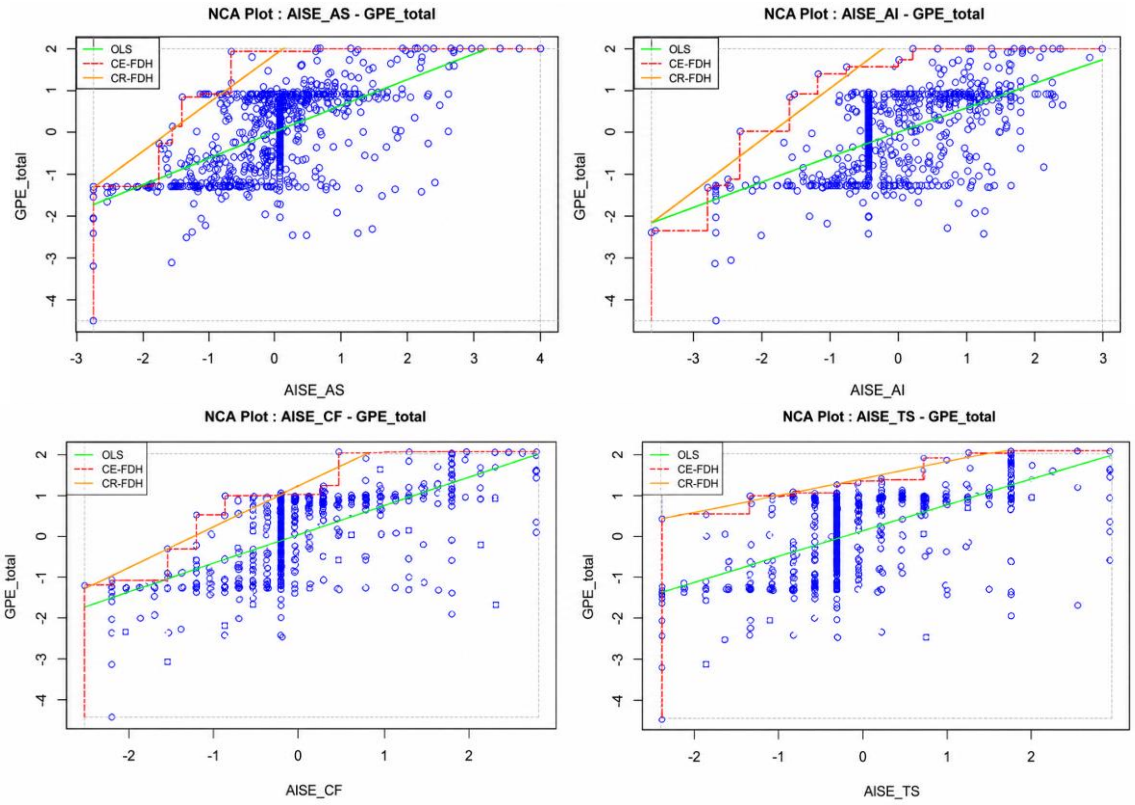

Figure 5. Scatter plot for dimensions of AISE and graduates' perceived employability.

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Under the CE-FDH method, all observations lie below the envelope, with an accuracy of 100%. In contrast, the accuracy of the CR-FDH method is slightly below 100%, with a small number of observations falling outside the regression upper line. However, the effect sizes obtained by the two methods are small, and the overall results are consistent. Therefore, a comparative report can be provided to enhance the robustness of the analysis.

4.3.2. Bottleneck Level Analysis

Bottleneck level analysis using CE-FDH represents the minimum level of a necessary condition required to achieve a specific outcome. For each expected outcome in the first column (Graduates' Perceived Employability, GPE), Table 7 shows the minimum values required for the predictor variables (AI self-efficacy and each of its dimensions). The results show that a level of 6.5% AI self-efficacy is required to achieve 50% perceived employability, meaning that even a moderate level of perceived employability cannot be achieved if AI self-efficacy does not reach the minimum level (6.5%). Of the four dimensions of AISE, achieving 50% perceived employability requires 1.1% assistive efficacy, 11.9% anthropomorphic interaction efficacy, and 2.6% comfort with AI efficacy. To achieve the highest level of perceived employability (90%-100%), the minimum requirements for the four dimensions of AISE are 42.6%, 51.8%, 63.1%, and 78.4%, respectively.

Table 7. Bottleneck level analysis results (CE-FDH).

GPE	AISE-total	AS	AI	CF	TS
0	NN	NN	NN	NN	NN
10	NN	NN	NN	NN	NN
20	NN	NN	NN	NN	NN
30	NN	NN	NN	NN	NN
40	NN	NN	3.9	NN	NN
50	6.5	1.1	11.9	2.6	NN
60	18.9	9.4	19.8	14.7	NN
70	31.3	17.7	27.8	26.8	NN
80	43.7	26.0	35.8	38.9	17.6
90	56.1	34.3	43.8	51.0	48.0
100	68.5	42.6	51.8	63.1	78.4

Note: NN is unnecessary.

5. DISCUSSION AND CONCLUSION

This study expands the research paradigm of perceived employability in the field of career development in higher education by integrating PLS-SEM and NCA (Necessary Condition Analysis) methods. In the context of AI-assisted employment, graduates enhance their employability through career preparation tools such as AI resume optimization, AI mock interviews, and AI job matching. This study systematically reveals the mechanism of action between behavioral beliefs (perceived ease of use and perceived usefulness), AI self-efficacy, and perceived employability. Compared to previous studies that mainly explored the "sufficiency relationship" between variables based on SEM, this study further introduces the NCA method to identify the key bottleneck factors required to achieve higher perceived employability in the context of the integration of AI into employment from the perspective of "necessary conditions". By simultaneously examining sufficiency and necessary conditions, this study not only deepens the understanding of the formation mechanism of AI-enabled employability but also provides methodological and practical insights for building an AI-supportive career development environment with the core objective of enhancing graduates' employment confidence.

The results indicate that, in AI-assisted career preparation scenarios, there is a significant positive relationship between graduates' behavioral beliefs (perceived usefulness and perceived ease of use) and perceived employability (GPE). This finding is consistent with existing research from the perspectives of cognitive psychology and technology acceptance, namely that perceived usefulness and ease of use of technology can reinforce an individual's ability

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judgment through cognitive appraisal processes [4, 6]. However, unlike previous studies that mainly focused on "willingness to use technology" or "learning performance," this study extends the outcome variables to core psychological indicators of career development, such as career exploration and career commitment, and further sheds light on the psychological mechanisms underlying the use of AI technology in the context of employment preparation. Furthermore, artificial intelligence self-efficacy (AISE) plays a partial mediating role between behavioral beliefs and GPE. This mechanism echoes [56]'s theory on the formation mechanism of self-efficacy and the research findings of Compeau and Higgins [39] on technological self-efficacy [39, 56]. However, compared to previous studies, this study embeds this classic self-efficacy theory into intelligent decision-making applications, revealing that AI not only exists as a tool but also participates in the employment competence construction process as a "cognitive enhancement environment." To further clarify the internal psychological structure of AISE in AI-assisted employment scenarios, this study subdivides it into four dimensions as single mediating variables, examining their relative roles in the relationship between behavioral beliefs and GPE. Compared to existing studies that typically treat AISE as a single latent variable, this study employs a multidimensional structural analysis method to reveal the differentiated contributions of different psychological components in the mechanistic pathway [57]. This multidimensional approach provides a more nuanced understanding of AI self-efficacy in the context of AI-supported career preparation [58].

In addition to the sufficiency path revealed by PLS-SEM, this study further uses necessary condition analysis (NCA) to support Hypothesis 5. The results show that AISE not only significantly affects GPE through mediating pathways but also exhibits a necessary characteristic when reaching higher GPE levels. In other words, in AI-assisted career preparation scenarios, if graduates' AI self-efficacy does not reach a certain threshold, it is difficult to achieve a high level of perceived employability. For example, achieving an 80% GPE level requires at least 43.7% AISE. Furthermore, the dimensional analysis shows that each dimension is necessary for achieving a higher level of GPE. This means that different psychological components influence GPE through their specific pathways and may form their own "bottleneck constraints" in achieving high-level employability. This study reveals the dual function of AISE in AI-assisted employment contexts. It serves both as a mechanism for promoting GPE and as an indispensable foundation for achieving higher perceived employability. This finding significantly differs from previous research traditions that relied solely on structural equation modeling to examine the "net effect" between variables [59]. This dual "sufficiency-necessity" framework allows for a more comprehensive understanding of the mechanism by which AI plays a role in career readiness. Specifically, PLS-SEM explains "how AISE enhances GPE," while NCA (Necessary Condition Analysis) answers "whether it is possible to achieve a high GPE in AI-assisted employment contexts without AISE." The combination of these two approaches not only enhances the robustness of the conclusions but also expands the analytical paradigm for AI empowerment mechanisms in higher education career development research.

This study reveals a new development path for career planning in higher education within the context of the deep integration of AI into the employment service system and redefines the functional positioning of AI in career development education. In AI-driven employment scenarios, intelligent tools such as AI mock interviews, intelligent resume optimization, and job matching systems should not merely be viewed as technical platforms that provide information or feedback but should instead be integrated into a normalized training environment within the process of cultivating professional skills. Through continuous, repetitive, and contextualized AI interaction, students can engage in expression training, job matching tests, and skills reflection in a low-risk environment, thereby gradually enhancing their employment confidence and competence awareness in employment practice. Simultaneously, AI should also become an important auxiliary tool for university career counselors. In actual counseling, AI systems can quickly analyze students' competency profiles, degrees of job matching, and development paths, providing counselors with data support and a diagnostic basis, thereby improving the accuracy of personalized guidance. This "human-machine collaboration" model can improve counseling efficiency while retaining the irreplaceable emotional support

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and value guidance functions of career counseling. This further promotes the shift in higher education career development education from "tool introduction" to "ecological reconstruction," achieving a more intelligent, continuous, and personalized employment support environment.

It is important to emphasize that when introducing AI to assist graduates in employment, universities should simultaneously provide operational training, case demonstrations, and practical guidance to reduce technical anxiety and enable students to develop a stable sense of AI self-efficacy through repeated use. Especially for students with weak technical confidence or who are not comfortable with AI interaction, targeted guidance and support should be provided to prevent them from giving up due to frustration in the early stages of use. Additionally, from the perspective of decision intelligence theory, AI self-efficacy is not a substitute variable for traditional career ability-building paths, but rather a capability amplification mechanism formed after being embedded in an intelligent decision-making environment. Even in the absence of AI support, graduates can still improve their employability through experience accumulation or social capital. However, in intelligent decision-making scenarios, AI self-efficacy constitutes a necessary threshold for achieving a high level of perceived employability. It promotes a higher-order leap in employability development by enhancing information processing efficiency, optimizing career decision-making quality, and improving the level of trust in human-computer interaction. This study further refines the "hidden bottlenecks" that certain shortcomings in AISE may cause. Universities can identify students' weaknesses in assistive function understanding, human-like interaction adaptation, or technological confidence through diagnostic assessments and intervene through tiered training. For example, embedding a self-assessment module into the employment service system can automatically recommend practice tasks of varying intensities based on students' AI proficiency, ensuring that students reach the basic competency level required to support higher employability.

While this study reveals the mechanisms underlying behavioral beliefs, AI self-efficacy, and perceived employability in AI contexts, several limitations remain. First, the sample source is relatively concentrated, and the external validity of the results needs further validation in different regions and types of universities. This study relied on self-report questionnaire data. Future research could incorporate behavioral data, such as AI platform usage frequency, modification frequency, and interview score changes, or longitudinal designs to enhance the robustness of causal inferences. Finally, although this study analyzed the sufficiency and necessity relationship using PLS-SEM and NCA, the variable structure is still based on a pre-existing theoretical framework. Future research could further explore the differentiated roles of different types of AI tools in career preparation to deepen the understanding of the complexity of AI contexts. It should be noted that as this study utilises cross-sectional data, the above results should be interpreted as statistical associations between variables and should not be regarded as causal relationships. In addition to the variables examined in this paper, factors such as prior experience of using AI, digital skills, career motivation, and other individual differences may also influence both AI self-efficacy and perceived employability simultaneously. Therefore, future research could employ longitudinal or experimental designs to further examine the temporal sequence and causal relationships among these variables.

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Transparency: The authors state that the manuscript is honest, truthful, and transparent, that no key aspects of the investigation have been omitted, and that any differences from the study as planned have been clarified. This study followed all writing ethics.
Competing Interests: The authors declare that they have no competing interests.
Authors' Contributions: All authors contributed equally to the conception and design of the study. All authors have read and agreed to the published version of the manuscript.
Disclosure of AI Use: The authors used OpenAI's ChatGPT to edit and refine the wording of the Introduction. All outputs were reviewed and verified by the authors.

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