Li et al. BMC Psychology (2025) 13:454
https://doi.org/10.1186/s40359-025-02757-2

BMC Psychology

RESEARCH

Open Access

Mediating effect of AI attitudes and AI literacy on the relationship between career self-efficacy and job-seeking anxiety

Ruihua Li[1], Sha Ouyang[2*] and Jianwei Lin[1*]

Abstract

As artificial intelligence (AI) technology quickly grows, college students have new worries and fears. Using Marx's theory of labour alienation, this study explores the complex relationship between college students' job-seeking anxiety (JSA) and career self-efficacy (CSE) in the context of the AI era. A structural equation modeling (SEM) study of data from 455 Chinese students indicates that CSE adversely affects JSA. Moreover, AI attitudes (AIA) and AI literacy (AIL) play significant mediating roles in the relationship between career self-efficacy (CSE) and job-specific anxiety (JSA). Specifically, these factors help explain how CSE influences JSA by fostering positive perceptions of AI and improving students' understanding of AI technologies. The findings underscore the importance of cultivating positive attitudes toward AI, enhancing AI literacy, and strengthening career self-efficacy to reduce job-seeking anxiety and better prepare students for the challenges of an AI-driven job market. These observations provide significant implications for educators and policymakers in developing interventions to enhance students' career preparedness and protect their mental health during technological changes.

Keywords Career self-efficacy, Job search anxiety, AI attitudes, AI literacy, University student employment

Introduction

In recent years, the employment difficulty for college graduates has become increasingly prominent. According to statistics from the Chinese Ministry of Education (2023), the number of college graduates is expected to reach 11.79 million in 2024, intensifying competition in the job market [1]. Meanwhile, the rapid advancement of artificial intelligence (AI) technology has profoundly impacted the employment market. The development of AI technology has prompted the upgrading and transformation of industrial structures. This shift has redefined the knowledge and skills students need to lead fulfilling lives and work efficiently [2]. While AI technology brings numerous new employment opportunities, it also poses significant challenges to traditional employment models [3].

As an emerging and rapidly evolving technology, artificial intelligence (AI) has garnered significant attention due to its complexity and advancement. Most studies consistently suggest that AI is expected to reduce certain types of jobs while simultaneously creating or transforming others, thereby reshaping the labour market in the future [4, 5]. The widespread application of AI technology poses a risk of replacing certain traditional occupations [6].

*Correspondence:
Sha Ouyang
shaouyang6@gmail.com
Jianwei Lin
Jianwei_lin@126.com
[1]Faculty of Basic Education, Putian University, Putian, Fujian, China
[2]The College of Marxism, Shaanxi Railway Institute, Weinan, Shaanxi, China

Marx's theory of labour alienation describes how workers can feel disconnected from their work in four key ways: alienation from what they produce (workers lack control over the goods or services they create), alienation from the work process (work becomes repetitive or meaningless), alienation from their human potential (work stifles creativity and growth), and alienation from others (work undermines relationships with colleagues or society) [7]. In the age of artificial intelligence (AI), these forms of alienation are becoming more severe. AI technologies, for instance, increasingly separate workers from the outcomes of their labour—such as when algorithms dictate work outputs—while automating tasks in ways that strip work of its purpose [8]. Human collaboration is also weakened as digital tools replace interpersonal interactions, and workers may feel further detached from their potential as AI overshadows creative or skill-based roles [9]. These shifts amplify students' uncertainty and anxiety when entering the job market, particularly as technical challenges—like adapting to rapidly evolving AI tools—disrupt traditional learning and skill development [10]. Moreover, the pervasive use of digital platforms and AI fosters a sense of powerlessness, with individuals struggling to retain autonomy in a technology-driven labour market, ultimately deepening feelings of oppression and loss of initiative [11, 12]. Given these characteristics of the current era, university students face intense job market competition and must continuously enhance their skills to adapt to technological changes.

Career self-efficacy (CSE), as an essential psychological resource, is considered crucial in helping university students cope with job-seeking anxiety (JSA) and enhancing their career adaptability. CSE is an individual's confidence in their ability to perform career-related tasks—such as planning, decision-making, and achieving goals—grounded in their self-awareness and career objectives [13, 14]. A robust body of research underscores the inverse relationship between Career Self-Efficacy (CSE) and Job-Seeking Anxiety (JSA). Numerous studies have established a negative correlation between these two constructions, indicating that higher levels of CSE are associated with lower levels of JSA. Research by Sawitri and Creed [15] highlights that individuals with higher job search self-efficacy are more likely to engage in proactive job search behaviours, reducing anxiety associated with job seeking. This aligns with Razak's assertion that increased self-efficacy can decrease anxiety levels, particularly when individuals feel supported in their job search efforts [16]. The interplay between self-efficacy and anxiety is further supported by Lent et al., who propose that self-efficacy is a foundational element in proactive career behaviours, which can mitigate anxiety during job searches [17]. However, these findings are predominantly rooted in traditional employment frameworks, where labour markets are relatively stable and human-centric. The advent of AI has disrupted these dynamics, introducing novel stressors—such as algorithmic hiring bias [18, 19], rapid skill obsolescence [20], and automation-driven job displacement [21]—that amplify JSA in ways unaccounted for by prior research.

Research also shows that although most students have limited knowledge and experience with AI, they generally hold positive and supportive attitudes toward its application in their fields of study [22]. The most common concern is the potential rise in unemployment rates associated with using AI [23]. This discomfort with labour alienation and the desire to adapt to it makes exploring CSE's impact on JSA in the AI era even more critical. Understanding and alleviating university students' career selection anxiety in the AI age is essential, requiring close attention and support from policymakers and educators to help students better adapt to the rapidly changing job market.

However, no empirical research has directly examined how CSE mitigates JSA within AI-disrupted contexts, nor whether AI Attitudes (AIA) and AI Literacy (AIL) mediate this relationship. This gap is particularly critical because traditional CSE frameworks may not fully account for the psychological challenges posed by AI's unpredictability, leaving students underprepared for the evolving labour market. Consequently, the present study investigates the chain mediation role of AIA and AIL in the relationship between CSE and JSA, offering theoretical insights and practical strategies to enhance university students' career adaptability in the AI era.

Literature review

Labor alienation theory and job-seeking anxiety

Marx's labour alienation theory elucidates how AI-driven job markets exacerbate job-seeking anxiety (JSA) through four interconnected dimensions: [1] product alienation, where AI automation strips individuals of control over outcomes (e.g., algorithmic hiring), weakening career self-efficacy (CSE) unless countered by AI literacy (AIL) to reframe AI as a tool; [2] process alienation, as rigid, AI-mediated workflows (e.g., automated assessments) erode autonomy, heightening anxiety unless adaptive AI attitudes (AIA) foster proactive engagement; [3] human essence alienation, where AI's displacement of creative tasks devalues uniquely human skills, necessitating strong CSE to reclaim purpose through AI-integrated competencies; and [4] interpersonal alienation, as AI-driven systems isolate job seekers, intensifying JSA unless AI literacy/attitudes enable new collaborative norms [9]. In contemporary society, especially with the deep integration of digital technology and capital, the phenomena of labour alienation have become increasingly severe, profoundly impacting the JSA of university students.

The extensive application of digital technology has accelerated information dissemination, leading to the rapid spread of anxiety on social media and information-sharing platforms [24]. Issues related to employment, marriage, and housing swiftly circulate among the youth, creating and exacerbating JSA. The propagation of online sentiments further fuels JSA [25, 26].

The rapid development of generative AI has further exacerbated JSA among college students by transforming interaction, cognition, and labour dynamics in ways that intensify uncertainty. For instance, real-world social exchanges are increasingly supplanted by AI-mediated communication, which can abstract interpersonal contact into digital signals and contribute to feelings of identity loss, immersion, or transgression in virtual spaces [27, 28]. This shift raises concerns about how best to present oneself to potential employers when AI-powered screening tools and online platforms replace face-to-face interactions. Additionally, cognitive demands evolve as generative AI automates or augments tasks that once required human insight, prompting students to question whether their skill sets remain relevant in rapidly changing industries [29, 30]. In terms of labour, generative AI reconfigures workflows and job roles—some positions may become obsolete while new, AI-centric roles emerge—feeling anxiety over employment stability. Notably, the integration of explainable AI (XAI) has been shown to mitigate some of these negative experiences by providing greater transparency into AI's decision-making processes, thereby reducing users' uncertainty and restoring trust [31]. Real-world social interactions are replaced by digital exchanges, resulting in the electronification and flattening of social interactions. With the widespread application of virtual reality technology, individuals in the real world are gradually alienated into "objects," "data," and "nodes" in the virtual world. Data discrimination and algorithmic recommendations introduce new threats to social interactions, exacerbating social inequality. The invisible discipline imposed by powerful computational capabilities restricts individual freedom, increasing uncertainty and anxiety among college students in the job market [26, 32].

From the perspective of Marx's theory of labour alienation, the development of artificial intelligence exacerbates the estrangement between labour products and labourers, between the labour process and labourers, and between interpersonal relationships [9]. College students facing highly automated and technology-driven work environments often feel replaced by machines, losing control over their work. This experience not only undermines their CSE but also intensifies their JSA.

Specifically, the development of AI leads to the alienation of labour products from labourers, causing college students to feel a lack of control over the outcomes of their work, thereby increasing uncertainty about their future careers [33]. Additionally, the alienation of the labour process results in a loss of self-identity and autonomy in the workplace, heightening anxiety during career decision-making. The alienation of interpersonal relationships makes college students feel isolated and unsupported in a highly competitive job market, further aggravating their JSA. AI systems' ethical compliance and decision-making behaviours are crucial in building human trust. For example, research has shown that in scenarios where robots adhere to moral principles, their obedience and protective behaviours are more conducive to enhancing human-robot trust [34].

Therefore, labour alienation exacerbates college students' JSA in the era of AI. This is not only due to the threat of unemployment brought about by technological advancements but also because of the profound impact of technology on the labour process and labour relations. Understanding this context is crucial for mitigating the JSA among college students.

Career self-efficacy and job-seeking anxiety

Self-efficacy refers to individuals' belief in their capabilities to organize and execute actions required for desired outcomes [35, 36]. Career Self-Efficacy (CSE) builds upon the broader concept of self-efficacy from Social Cognitive Theory, focusing specifically on individuals' confidence in handling career-related tasks [37]. The idea of CSE was developed within the Social Cognitive Career Theory (SCCT) framework by Lent, Brown [38].

Individuals with high career self-efficacy typically exhibit greater achievement motivation and actual accomplishments during their career exploration process [39]. In studies on the CSE of university students, scholars have found that students with low self-efficacy levels tend to avoid careers they believe they are not competent in, while those with high self-efficacy levels are more likely to actively seek out and obtain various career information, thereby expanding their range of career choices [40]. Individuals with high occupational self-efficacy would have more confidence in their careers, have more active job-seeking behaviours, have stronger career decision-making abilities, and have a higher level of career maturity [41, 42]. Research has also shown that CSE indirectly influences emotional experiences by modulating negative emotional expectations and coping strategies, thereby reducing JSA [43–45].

Research shows that increased career self-efficacy is linked to reduced job-seeking anxiety. For example, Deer, Gohn [46] highlight that bolstering self-efficacy during career preparation among college students can boost job search intentions and diminish anxiety levels. In a similar vein, Razak [47] found that individuals with higher self-efficacy report lower levels of employment-related anxiety, especially when they perceive ample career opportunities. From the perspective of labour alienation theory, workers feel deprived and estranged during the alienated labour process [7]. This phenomenon potentially links with CSE, leading individuals to lose self-identification and control in their work, weakening their CSE. When confronted with highly automated and technologically driven work environments, workers often feel replaced by machines, losing control over their work [48, 49]. This experience further exacerbates JSA.

Career self-efficacy, artificial intelligence attitudes, and job-seeking anxiety

High levels of professional self-efficacy (SCE) are linked to proactive and confident career management, which can influence the adoption of emerging technologies. Individuals with strong self-efficacy tend to view technological innovations, such as artificial intelligence (AI), as opportunities rather than challenges. This viewpoint is supported by Ramasamy and Nithyanandan, who assert that positive psychological factors, including self-efficacy, significantly impact student career development behaviours [50]. Additionally, research by Van Ryn and Vinokur indicates that higher career self-efficacy correlates with increased job search activities and favourable employment outcomes [51], reinforcing the idea that self-efficacy drives proactive career management strategies [52]. Moreover, individuals with high SCE will likely perceive AI as a beneficial tool that enhances their job search strategies and career development opportunities [53, 54]. Bi, Mou [52] further explains that self-efficacy in career decision-making shapes individuals' perceptions and attitudes toward career-related challenges, including technology integration.

JSA, which is characterized by feelings of apprehension and uncertainty during the job search process, can be alleviated by positive attitudes toward AI. When individuals view AI as a supportive resource rather than a complicated factor, they are likely to experience lower anxiety levels. Research shows that a favourable attitude toward technology can boost confidence in using digital tools to address work-related challenges, thus reducing anxiety [55]. For instance, Sun [56] illustrates that self-efficacy is a mediating factor in career aspirations, suggesting that confidence in one's abilities can mitigate anxiety during the job search.

The proposed mediational model suggests that attitudes toward artificial intelligence (AIA) act as the mechanism through which SCE affects JSA. Specifically, individuals with high SCE are more inclined to develop positive attitudes toward AI, which fosters a constructive perspective on technology-driven recruitment processes. This is supported by Kong's findings, which highlight the beneficial effects of AI perception on career resilience and initiative, indicating that a favourable view of AI empowers individuals to navigate the complexities of the job market [57]. Therefore, confidence in one's career abilities promotes a positive perception of AI and alleviates anxiety during the job search process.

Career self-efficacy, artificial intelligence literacy, and job-seeking anxiety

AI literacy encompasses the skills and knowledge necessary to understand, evaluate, and effectively utilize artificial intelligence (AI) technologies. This competency includes familiarity with fundamental AI concepts, the ability to assess AI applications critically, and the capacity to apply these technologies to solve real-world problems. Research indicates that individuals with high career self-efficacy (SCE) are more likely to invest in developing new technical skills, including AI literacy. For instance, confident job seekers tend to be more motivated to enrol in AI-related courses, attend workshops, or engage in self-directed learning to enhance competitiveness [58]. This proactive approach to education, driven by high SCE, is crucial for acquiring the technical skills required in today's job market. Job-seeking anxiety (JSA) often arises from uncertainties about the skills needed for success in a technology-driven environment [59]. However, individuals with strong AIL are better equipped to navigate these challenges confidently. Empirical evidence suggests that improved technical literacy can alleviate anxiety by bridging the gap between one's existing skill set and market demands [60]. As job seekers become more proficient in AI, they better understand how to adapt and utilize AI tools, which helps reduce feelings of uncertainty and stress.

The proposed mediation model posits that AIL is a critical intermediary through which SCE influences JSA. In this framework, individuals with high SCE are more inclined to pursue and cultivate AIL, which subsequently helps mitigate JSA by equipping them with the technological skills essential for success in a digital economy. While direct empirical tests of this mediation model are still emerging, related research has indirectly supported it by demonstrating that technical literacy can buffer against job-related stress and anxiety. These findings highlight the potential role of AIL as a vital mediator in enhancing job seekers' preparedness and reducing their concerns about entering a technologically advanced workforce.

The chain mediating role of artificial intelligence attitudes and artificial intelligence literacy

AI is regarded as a computer system capable of performing tasks that require human intelligence. These systems can autonomously perceive their environment, analyze abstract models, and make decisions based on reasoning

(OECD). The rapid development of AI technology has profoundly impacted the labour market. Research indicates that AI affects the labour market in two primary ways: the substitution effects and the compensation effects [61]. In terms of the substitution effect, while automation and computation have increased labour productivity, they have also reduced the demand for labour, thereby increasing the risk of job displacement. Robots can replace low-skilled and high-skilled jobs under certain conditions, reducing labour demand and lowering wages.

On the other hand, the compensation effects of AI also significantly impact the labour market. Yang, Nie [62] explored the capitalization effect within Schumpeter's endogenous growth framework, suggesting that AI increases the returns from establishing production units, raising profits, creating new jobs, and attracting additional labour. Restrepo [63] presented an employment creation model indicating that while automation eliminates specific jobs, it generates new jobs that offer comparative advantages. These dual effects of substitution and compensation significantly shape university students' AIA. AIA refers to individuals' perceptions and emotional responses to AI technologies and their applications [64].

AI literacy (AIL) refers to university students' understanding and ability to apply artificial intelligence technologies. In this context, we differentiate between two interconnected concepts: [1] AI literacy (AIL), which encompasses students' technical skills and practical competencies with AI, and [2] interest in and acceptance of AI-related careers, which reflects their willingness to explore professional paths in the AI sector [65]. Fostering students' interest in AI careers can indirectly enhance AIL by encouraging deeper engagement with AI learning and its applications. Higher levels of AIL enable students to adapt more effectively to technological advancements and alleviate job-seeking anxiety (JSA) [66]. Students with higher AIL exhibit lower anxiety levels during career selection because they can better understand and utilize AI technologies, facing employment challenges posed by AI with more composure and confidence. Studies have found a significant positive correlation between students' AIA and their levels of AIL [67, 68].

According to the theory of labour alienation, technological advancements can lead to the alienation of the labour process, potentially affecting workers' attitudes and acceptance of technology [69]. When students' CSE is influenced by labour alienation, it can impact their JSA. Furthermore, students may develop conflicting attitudes toward AI when they perceive that AI technologies dominate and control their labour process. Once individuals lose control over technology, their interest in and enhancement of AIL can diminish.

Several studies have examined the relationship between university students' CSE and JSA [11, 70–72]. However, limited research has investigated this relationship within the context of AI. This study explores the impact of CSE, AIAI, and AIL on JSA among university students from the perspective of labour alienation theory. It further examines the mediating role of AIA and AIL in the relationship between CSE and JSA, ultimately revealing how CSE influences students' JSA in an AI-driven context.

To better understand the relationships between CSE, AIA, AIL, and JSA, this paper proposes a chain mediation model in Fig. 1. This model explores how CSE influences JSA among university students through the mediating roles of AIA and AIL.

First, as a source of self-evaluation and confidence, CSE can directly influence an individual's confidence in career

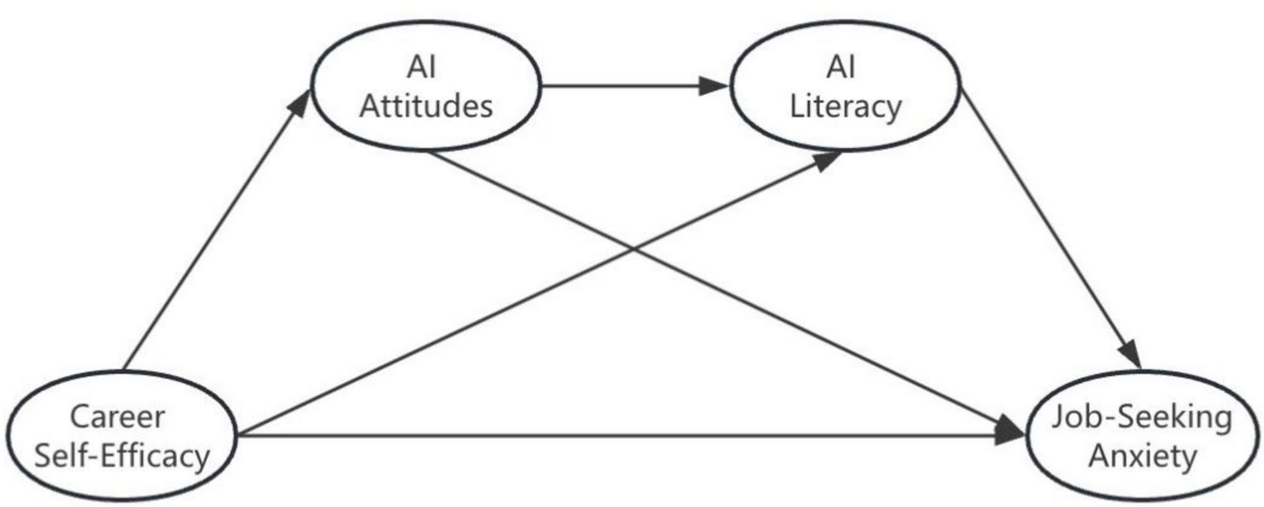

Fig. 1 The hypothetical model among variables

choices and anxiety levels. Therefore, we hypothesize the following:

Hypothesis 1 CSE negatively affects JSA.
Marx's labour alienation theory shows a negative relationship between Career Self-Efficacy (CSE) and Job-Seeking Anxiety (JSA). Less attention has been paid to the mechanisms through which CSE influences JSA—particularly in contexts involving artificial intelligence (AI). Mediation analysis is ideal for uncovering the pathways by which an independent variable (CSE) exerts its effect on a dependent variable (JSA) through one or more mediating variables [73].In traditional employment settings, various psychological and contextual factors have been shown to mediate the link between self-efficacy and anxiety-related outcomes [74, 75]. However, AI Attitudes (AIA) and AI Literacy (AIL) remain primarily unexplored as potential mediators despite their growing relevance in technologically advanced job markets. By examining how AIA and AIL operate as chain mediators, we can gain deeper insight into whether and how positive attitudes and greater familiarity with AI transmit the protective effect of high CSE onto lower JSA. This approach extends our understanding of the CSE–JSA relationship and underscores the unique role of AI-related factors in shaping career development outcomes. Following Baron and Kenny's (1986) conceptual and statistical guidelines, we test whether AIA and AIL explain the indirect effect of CSE on JSA. Our mediation framework thus addresses an identified gap in the literature by linking individual self-belief (CSE) with emerging technological competencies (AIL) and attitudes (AIA), ultimately affecting how university students cope with job-market uncertainties in the AI era. Therefore, we hypothesize:

Hypothesis 2 AIA mediates the relationship between CSE and JSA.
AIL, as a second mediating variable, directly impacts an individual's anxiety levels during the career selection process [76]. Individuals with higher AIL are better able to adapt to technological changes. When facing employment challenges brought about by AI technology, they exhibit more calmness and confidence, thereby reducing JSA [77]. Therefore, we hypothesize:

Hypothesis 3 AIL mediates the relationship between CSE and JSA.
When individuals hold positive AIA, they are more likely to learn and master AI technology, thereby enhancing their AIL [22]. According to the technology acceptance theory, a positive attitude reduces their concern about AI replacing human jobs and increases their confidence and interest in AI-related careers. Therefore, we hypothesize:

Hypothesis 4 AIA and AIL play a chain-mediating role in the relationship between CSE and JSA.

Through this chain mediation model, we can systematically explore the complex relationships among CSE, AIA, AIL, and JSA. This helps reveal how CSE affects university students' JSA and provides valuable guidance for enhancing students' career adaptability in the AI era. It offers theoretical support and practical advice for university students' psychological counselling and career planning.

Methods

In this study, data were primarily collected via questionnaires and analyzed using SPSS and AMOS. Our objective was to test a model—derived from an extension of Marx's labour alienation theory—that examines how Career Self-Efficacy (CSE) affects Job-Seeking Anxiety (JSA) through the mediating effects of AI Attitudes (AIA) and AI Literacy (AIL). Given the confirmatory nature of our research, we employed covariance-based structural equation modelling (CB-SEM) via AMOS, which is well suited for theory testing and rigorous evaluation of model fit and construct validity [78, 79]. With a sample of 455 participants and 15 sub-variables, our data not only meets the sample size requirements of CB-SEM (typically 10–20 observations per free parameter are recommended) but also satisfies the multivariate normality assumption, which provides a crucial basis for reliable parameter estimation and model fit assessment—. In contrast, partial least squares SEM is more appropriate for exploratory or prediction-focused studies. This integrated analytical approach ensures a robust framework that underpins our study's theoretical and empirical contributions.

Participants and procedure

This study received ethical approval from the Academic Committee of Shaanxi Railway Engineering Vocational and Technical College (approval number EPSRI2024-0501-0011), covering all aspects of participant recruitment, data collection, and data analysis at study sites in Shaanxi and Gansu provinces in China. All procedures adhered to human research guidelines, including the Declaration of Helsinki.

Data was collected from students at four universities in Shaanxi and Gansu provinces via an online survey administered through Wenjuanxing, with teachers assisting in questionnaire distribution. We employed convenience sampling, a non-probability sampling method where participants voluntarily responded to the study [80].

We acknowledge that convenience sampling introduces potential biases, such as self-selection bias, which may affect generalizability. However, given practical

Table 1 Sample composition

Projects	Categories	Cases	Percentage
Gender	Male	249	54.7
	Female	206	45.3
Educational Stages	Higher vocational College student	216	47.5
	Undergraduate student	104	22.9
	Postgraduate student	135	29.7
Grade	Freshman	104	22.9
	Sophomore	72	15.8
	Junior	91	20
	Senior	51	11.2
	Master	75	16.5
	PhD	62	13.6
Major	Humanities	90	19.8
	Natural Science	62	13.6
	Engineering	98	21.5
	Business Administration	55	12.1
	Arts	71	15.6
	Medical Sciences	45	9.9
	Other	34	7.5
Family Location	City	191	42
	Country	264	58

Data cleaning

constraints related to accessibility and resource limitations, this approach was the most feasible.

A total of 597 questionnaires were initially collected. After excluding responses with unusually short completion times or inconsistent patterns, 455 valid questionnaires were retained, yielding an effective response rate of 76.4%.

The sample size was determined based on structural equation modelling (SEM) analysis guidelines. Byrne and Kline recommend a minimum of 10–20 observations per free parameter, with 300–450 samples considered sufficient for complex models [78, 79].

The final sample included students from higher vocational colleges (47.5%), undergraduate programs (22.9%), and master's or doctoral programs (29.7%), with an urban-rural distribution of 42% urban and 58% rural. At a 95% confidence level, the margin of error is approximately ± 4.6%, supporting the statistical robustness of the results.

The demographic data of the respondents is summarized in Table 1. Among the 455 respondents, 249 were male (54.7%) and 206 were female (45.3%). The respondents represented diverse educational backgrounds: 47.5% were from higher vocational colleges, 22.9% from universities, and 29.7% were master's or doctoral students. Their academic disciplines included anthropology, natural sciences, arts, and medicine. Additionally, 42% of the respondents came from urban families, while 58% were from rural families. This balanced distribution

Table 2 VIF/TOL values

Variable	VIF/TOL (Model 1)	VIF/TOL (Model 2)	VIF/TOL (Model 3)	VIF/TOL (Model 4)
CSE	1.092/0.916	1.077/0.928	1.090/0.918	-
AIA	1.105/0.905	1.132/0.884	-	1.147/0.872
AIL	**1.118/0.895**	**-**	**1.119/0.894**	**1.120/0.893**
JSA	**-**	**1.129/0.886**	**1.104/0.906**	**1.147/0.872**

ensured that the findings reflected the diversity of students across urban and rural settings.

The urban-rural distribution is particularly relevant, as exposure to artificial intelligence (AI) and technology significantly differs between these settings. By capturing this diversity, the study improves the representativeness and accuracy of its findings, providing a robust basis for understanding the relationships explored in this research.

Before analysis, we performed comprehensive data cleaning to ensure data quality. We excluded questionnaires with unusually short completion times or inconsistent responses. Next, using AMOS, we computed Mahalanobis distances ($p < 0.001$) to identify and remove multivariate outliers and assessed multivariate normality by calculating Mardia's skewness and kurtosis via an online calculator (https://webpower.psychstat.org/models/kurtosis/), ensuring our dataset was suitable for further analysis.

The purpose of conducting multicollinearity diagnostics is to ensure that the independent variables in our models are sufficiently distinct. This is important because high multicollinearity can compromise parameter estimates' stability and overall interpretability of structural equation models [81].

As shown in Table 2, Variance Inflation Factor (VIF) values across Models 1 through 4 for the key variables—Career Self-Efficacy (CSE), Attitude toward AI (AIA), AI Literacy (AIL), and Job Selection Anxiety (JSA)—are consistently low, ranging from 1.077 to 1.147. Corresponding Tolerance (TOL) values range between 0.872 and 0.928. These results are well within acceptable thresholds for assessing multicollinearity. According to [82], a VIF value greater than 3.3 in the PLS-SEM context may indicate full collinearity issues. Moreover, a TOL value below 0.10 typically indicates multicollinearity concerns [81]. Since all VIF values in our study are substantially below 3.3, and all TOL values are above 0.87, we conclude that multicollinearity is not a concern, thereby supporting the reliability of our regression estimates and subsequent path modelling.

Measures

We employed four distinct research tools to gather comprehensive data and insights for our study, which are:

CSE scale

The Chinese version of the CSE scale is derived from the original scale developed by Taylor and Betz (1983), which consists of five dimensions and 50 items. In 2001, a short form was created, retaining the original five dimensions but reducing the number of items to 25. The short version, translated and validated by scholars in China, has demonstrated good reliability [83]. The dimensions are Self-Appraisal (SA), Gathering Occupational Information (IC), Goal Selection (TS), Making Plans (MP), and Problem Solving (PS). The questionnaire uses a five-point Likert scale, with subjects rating each item from "1. not at all confident" to "5. completely confident."

AIA scale

The AIA Scale, developed by Schepman and Rodway [84], was designed to measure a range of attitudes towards artificial intelligence. The validated scale includes two main dimensions—positive attitudes (PA) and negative attitudes (NA)- and encompasses 20 items. Each item is rated on a five-point Likert scale, from "1. Strongly Disagree" to "5. Strongly Agree." The statements are designed to reflect general attitudes towards AI, not limited to specific applications, settings, or narrow time frames. Examples include "AI has many beneficial applications" and "I believe AI systems will make many mistakes."

AIL scale

The AIL Scale, developed by Hwang, Zhu [85], includes 19 items across four dimensions: Critical comprehension ability (CCA), ability to recognize the social impact of AI (RA), ability to utilize AI technology (UA), and ethical behaviour ability (EBA). All items are rated on a five-point Likert scale, measuring the self-perceived level of AI literacy. The scale ranges from "1. Strongly Disagree" to "5. Strongly Agree," with items such as "I can critically analyze content recommended by AI" and "I can adhere to ethical standards when using AI technology."

JSA scale

The JSA scale used in this study is the Chinese version revised and validated by Yuzhu; and Dewen [86]. The scale includes 26 items across four dimensions: competitive stress (CS), employment support (ES), lack of confidence (LC), and prospects concerns (PC). Respondents rate items on a five-point Likert scale, ranging from "1. Strongly Disagree" to "5. Strongly Agree." Sample items include concerns such as "Worrying about not finding a job due to insufficient employment information provided by the school" and "Worrying that my career aspirations may not be realized."

Table 3 Full collinearity testing

CSE	AIA	AIL	JSA
1.185	1.187	1.138	1.215

Measurement Model

Our analysis proceeded in three main stages: evaluation of the first-order measurement model, aggregation into second-order constructs, and assessment of the structural (path) model.

Data analysis

Common method bias

Given the self-reported nature of the data, we first examined potential common method bias (CMB). We first tested the issue of Common Method Bias by following the suggestions of Kock and Lynn [87] and Collier [88] by testing the full collinearity. In this method, all the variables will be regressed against a standard variable, and if the VIF ≤ 3.3, then there is no bias from the single source data. The analysis yielded a VIF of less than 3.3; thus, single-source bias is not a serious issue with our data (Table 3).

To assess the overall fit of the measurement models, we adopted a set of widely recommended fit indices following the guidelines of Hair, Risher [82]. These included the chi-square to degrees of freedom ratio (χ^2/df, acceptable range: 1–5), the Goodness-of-Fit Index (GFI, acceptable if > 0.80; good if > 0.90), the Root Mean Square Error of Approximation (RMSEA < 0.08), and the Root Mean Square Residual (RMR < 0.05). In addition, we considered incremental fit indices such as the Comparative Fit Index (CFI), the Incremental Fit Index (IFI), and the Tucker-Lewis Index (TLI), all of which are considered acceptable when exceeding the threshold of 0.90.

As summarized in Table 4, the results show that the first-order and second-order measurement models demonstrate an acceptable overall model fit. Specifically, while the GFI for the first-order model (0.806) is slightly below the ideal 0.90 threshold, it remains within the acceptable range for complex models. Furthermore, all other indices—including RMSEA, RMR, CFI, IFI, and TLI—satisfy or exceed the recommended cut-off values, thereby supporting the adequacy of the model structure.

Overall, the measurement model demonstrates robust reliability, convergent validity, discriminant validity, and excellent model fit, providing a solid foundation for

Table 4 Measurement model fit indices

	χ2/df	GFI	RMSEA	RMR	CFI	IFI	TLI
First Order Constructs Model	1.337	0.806	0.027	0.037	0.952	0.952	0.949
Second-order Constructs Model	2.686	0.938	0.061	0.035	0.940	0.940	0.924

aggregation into second-order constructs and further structural analysis.

We assessed the loadings, average variance extracted (AVE), and composite reliability (CR) for the measurement model. The load value should be ≥0.5, the AVE should be ≥0.5, and the CR should be ≥0.7. As shown in Table 5, the AVEs are higher than 0.5, and the CRs are higher than 0.7. The factor loadings range from 0.659 to 0.847, with most values exceeding 0.70. Although a few loadings (e.g., 0.659 and 0.661) fall slightly below the ideal threshold of 0.70, this is generally acceptable in empirical research [78]. We also assessed the validity and reliability of the second-order constructions, as shown in Table 6. The second-order measurements were also valid and reliable.

Then, in step 2, we assessed the discriminant validity using the HTMT criterion suggested by Henseler, Ringle [89] and updated by Franke and Sarstedt [90]. The HTMT values should be ≤0.85, the stricter criterion, and the mode lenient criterion is it should be ≤0.90. As shown in Table 7, the values of HTMT were all lower than the stricter criterion of ≤0.85. As such, we can conclude that the respondents understood that the nine constructions are distinct. Together, these validity tests have shown that the measurement items are valid and reliable.

In summary, the comprehensive CFA results and the reliability, convergent validity, and discriminant validity tests prove that the measurement model is reliable and valid. These findings support our adoption of a two-stage structural equation modelling (SEM) approach and offer a robust foundation for the subsequent analysis.

Results

Descriptive analysis and ANOVA of core variables

Descriptive statistics were conducted on the key variables, including CSE, AIA, AIL, and JSA, to understand the basic characteristics of the study sample and provide foundational data for subsequent analyses.

The descriptive statistics of the main variables in this study include Career Self-Efficacy (CSE), Attitude toward AI (AIA), AI Literacy (AIL), and Job Selection Anxiety (JSA). The mean scores of CSE (3.233), AIA (3.168), and AIL (3.190) suggest that students generally possess moderate to high confidence in their career-related abilities and hold positive attitudes toward AI. The mean score of JSA (2.746) indicates relatively low anxiety related to job selection. The standard deviations across variables are moderate, reflecting acceptable levels of variability in student responses.

To examine whether the data met the assumption of multivariate normality—an essential prerequisite for applying parametric statistical techniques such as structural equation modelling—we employed the WebPower calculator based on Mardia's multivariate skewness and kurtosis [10, 11]. The results indicated a Mardia's skewness value of 1.048 (χ^2 = 93.60, df = 120, $p > 0.05$) and a Mardia's kurtosis of 27.829 (z = 1.19, $p = 0.2344$). Both values fall within acceptable limits, indicating that the joint distribution of the four constructs approximates multivariate normality. To avoid conceptual ambiguity, we clarify that these results refer to multivariate, not univariate, normality.

To further explore the role of demographic variables, a one-way ANOVA was conducted using gender, education level, grade, major, and family region as independent variables. The results revealed no significant differences in AIA, AIL, or CSE across groups. However, education level significantly impacted.

Post hoc comparisons further indicated that PhD students reported significantly lower levels of JSA compared to Freshmen (mean difference = -0.312, S.E. = 0.096, $p = 0.015$), Juniors (mean difference = -0.298, S.E. = 0.104, $p = 0.047$), and Master's students (mean difference = -0.380, S.E. = 0.103, $p = 0.004$). JSA levels between PhD students and sophomores (mean difference = -0.241, $p = 0.142$) or Senior students (mean difference = -0.249, $p = 0.239$) were not statistically significant. These findings suggest that while PhD students experience lower job selection anxiety, statistically significant differences are only observed compared to certain education levels.

Path analysis and chain mediation model

To further examine the chain mediation effect of CSE on JSA through AIA and AIL, this study employed SEM using AMOS software and validated the results through the Bootstrap method. The Bootstrap method, a non-parametric resampling technique, was utilized to enhance the robustness and reliability of the findings by providing standard error (S.E.) and confidence intervals (CI) estimates through repeated sampling (10,000 times in this study).

Figure 2 illustrates the standardized path coefficients within the structural model, revealing the pathways between CSE, AIA, AIL, and JSA. According to the path analysis results, CSE significantly positively affects attitudes towards AIA with a standardized path coefficient of 0.37, indicating that higher CSE leads to more positive AIA among students. Similarly, AIA positively influences AIL with a standardized path coefficient of 0.23, suggesting that positive AIA is associated with higher levels of AIL. Additionally, CSE significantly positively affects AIL with a standardized path coefficient of 0.27, indicating that students with higher CSE are more proactive and effective in enhancing their AIL.

The path analysis (Table 8) reveals significant relationships among CSE, AIA, AIL, and JSA. Specifically, CSE significantly positively affects AIA ($\beta = 0.337$, $p < 0.001$), indicating that higher CSE corresponds to more positive

Table 5 Measurement model for the first order constructs

First Order Constructs	Indicator	Loadings	AVE	CR
SA	SA5	0.767	0.629	0.894
	SA4	0.838		
	SA3	0.822		
	SA2	0.817		
	SA1	0.697		
IC	IC5	0.689	0.61	0.886
	IC4	0.745		
	IC3	0.751		
	IC2	0.8		
	IC1	0.832		
TS	TS5	0.818	0.663	0.908
	TS4	0.798		
	TS3	0.816		
	TS2	0.847		
	TS1	0.743		
MP	MP5	0.668	0.529	0.848
	MP4	0.68		
	MP3	0.725		
	MP2	0.806		
	MP1	0.71		
PS	PS5	0.741	0.591	0.878
	PS4	0.808		
	PS3	0.759		
	PS2	0.693		
	PS1	0.775		
CCA	CCA5	0.709	0.577	0.872
	CCA4	0.774		
	CCA3	0.762		
	CCA2	0.753		
	CCA1	0.798		
PA	PA1	0.779	0.538	0.933
	PA2	0.759		
	PA3	0.774		
	PA4	0.767		
	PA5	0.722		
	PA6	0.744		
	PA7	0.748		
	PA8	0.718		
	PA9	0.686		
	PA10	0.661		
	PA11	0.69		
	PA12	0.745		
NA	NA1	0.668	0.504	0.89
	NA2	0.744		
	NA3	0.706		
	NA4	0.724		
	NA5	0.717		
	NA6	0.752		
	NA7	0.713		
	NA8	0.648		

Table 5 (continued)

First Order Constructs	Indicator	Loadings	AVE	CR
ES	ES1	0.734	0.675	0.943
	ES2	0.778		
	ES3	0.786		
	ES4	0.77		
	ES5	0.733		
	ES6	0.767		
	ES7	0.778		
	ES8	0.76		
RA	RA1	0.781	0.527	0.847
	RA2	0.746		
	RA3	0.674		
	RA4	0.732		
	RA5	0.69		
CS	CS1	0.765	0.681	0.914
	CS2	0.72		
	CS3	0.7		
	CS4	0.738		
	CS5	0.678		
EBA	EBA1	0.761	0.539	0.824
	EBA2	0.659		
	EBA3	0.735		
	EBA4	0.777		
UA	UA5	0.671	0.531	0.85
	UA4	0.713		
	UA3	0.741		
	UA2	0.774		
	UA1	0.74		
LC	LC1	0.815	0.726	0.949
	LC2	0.799		
	LC3	0.812		
	LC4	0.793		
	LC5	0.788		
	LC6	0.792		
	LC7	0.822		
PC	PC6	0.774	0.666	0.923
	PC5	0.786		
	PC4	0.769		
	PC3	0.782		
	PC2	0.715		
	PC1	0.705		

AIA among students. AIA, in turn, significantly influences AIL (β = 0.23, $p < 0.001$), suggesting that stronger AIA is associated with higher levels of AIL. Moreover, CSE exerts a significant positive impact on AIL (β = 0.243, $p < 0.001$), implying that students with higher CSE tend to be more proactive and effective in enhancing their AIL. Regarding JSA, AIL demonstrates a significant negative relationship (β = -0.205, $p < 0.001$), indicating that higher AIL corresponds to lower job selection anxiety. Finally, both CSE (β = -0.192, $p < 0.001$) and AIA (β = -0.268, $p < 0.001$) negatively affect JSA, suggesting that students with higher CSE or more positive AIA are likely to experience reduced job selection anxiety.

Additionally, AIL significantly negatively impacts JSA (β = -0.205, $p < 0.001$), indicating that students with higher AIL experience lower job selection anxiety. Likewise, the direct effect of CSE on JSA is significant (β = -0.192, $p < 0.001$), suggesting that students with higher CSE tend to have lower anxiety levels during the job-seeking process.

These findings, consistent with the stepwise mediation logic proposed by Baron and Kenny [91], strongly support the chain mediation model and highlight the

Table 6 Measurement model for the second order constructs

Second Order Constructs	Indicator	Loadings	AVE	CR
CSE	PS	0.753	0.501	0.833
	MP	0.718		
	TS	0.626		
	IC	0.699		
	SA	0.737		
AIA	PA	0.909	0.58	0.724
	NA	0.577		
AIL	CCA	0.834	0.519	0.81
	RA	0.609		
	UA	0.751		
	EBA	0.667		
JSA	CS	0.639	0.502	0.799
	ES	0.747		
	LC	0.615		
	PC	0.816		

Table 7 Discriminant validity (HTMT)

Constructs	1	2	3	4
CSE				
AIA	0.353			
AIL	0.329	0.358		
JSA	0.355	0.372	0.345	

importance of exploring how CSE influences JSA through AIA and AIL. Specifically, CSE significantly affects JSA ($\beta = -0.192$, $p < 0.001$) while also exerting significant effects

Table 8 Path analysis results

Path	STD.Estimate	Estimate	S.E.	CR.	*P*
CSE-> AIA	0.337	0.368	0.061	6.03	*P*<0.001
AIA-> AIL	0.23	0.231	0.067	3.436	*P*<0.001
CSE-> AIL	0.243	0.266	0.065	4.063	*P*<0.001
AIL-> JSA	-0.205	-0.15	0.044	-3.434	*P*<0.001
CSE-> JSA	-0.192	-0.153	0.048	-3.177	*P*<0.001
AIA-> JSA	-0.268	-0.196	0.053	-3.696	*P*<0.001

on both AIA ($\beta = 0.337$, $p < 0.001$) and AIL ($\beta = 0.243$, $p < 0.001$). In addition, AIA significantly influences AIL ($\beta = 0.23$, $p < 0.001$), and both AIA (β = -0.268, $p < 0.001$) and AIL (β = -0.205, $p < 0.001$) show negative relationships with JSA. These results align with Baron and Kenny's foundational criteria for establishing mediation, suggesting that AIA and AIL may mediate the relationship between CSE and JSA [91].

Then, we employed the bootstrap method advocated by Preacher and Hayes [92] to obtain more accurate estimates of the indirect effects. Bootstrapping not only estimates standard errors and confidence intervals through thousands of resamples—enhancing the precision of mediation results—but also avoids the normality assumptions inherent in traditional parametric tests.

As shown in Table 9, our bootstrap analysis (10,000 resamples) reveals a significant adverse indirect effect of CSE on JSA through both AIA and AIL, as well as through the chain mediation path (CSE → AIA → AIL →

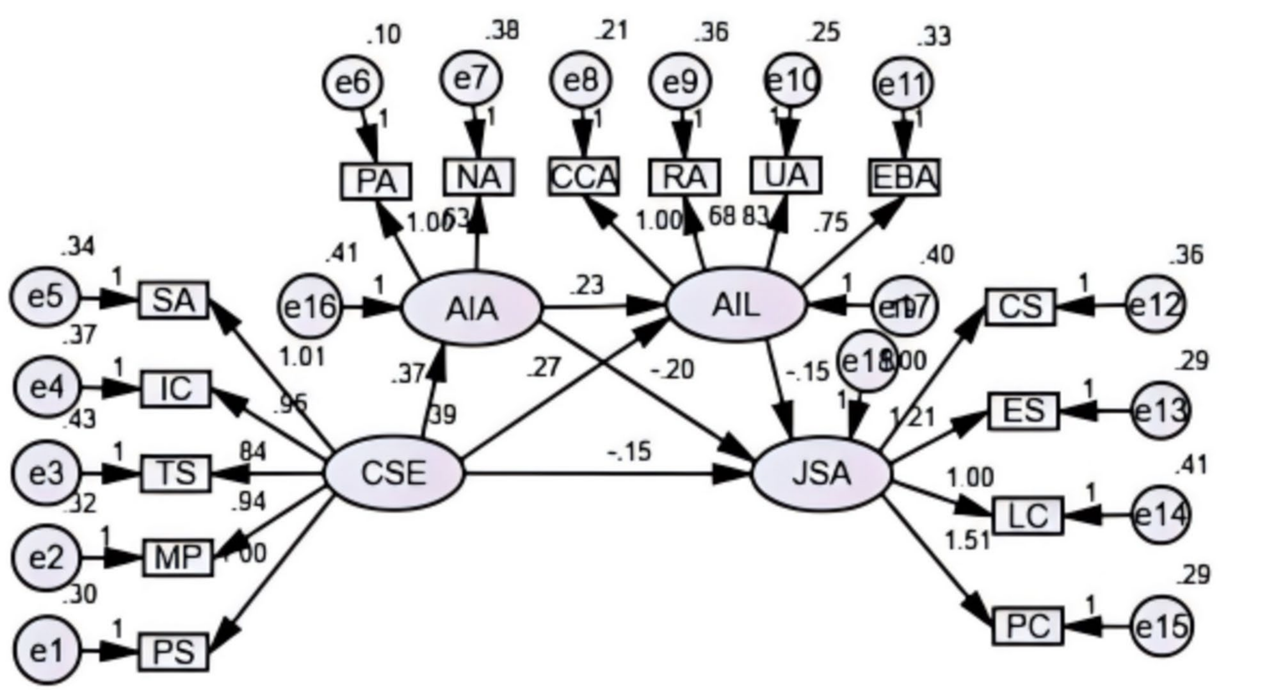

Fig. 2 Standardized Path Coefficients between Variables

Table 9 The effect and efficiency ratio of the chain mediation model

Path	Effect	Estimate	Lower	Upper	*P*
CSE→AIA→JSA	Indirect Effect	-0.072	-0.139	-0.036	$p<0.001$
CSE→AIL→JSA	Indirect Effect	-0.04	-0.088	-0.012	$p<0.001$
CSE→AIA→AIL→JSA	Indirect Effect	-0.013	-0.04	-0.002	$p<0.001$
CSE→AIA→AIL→JSA	Total Effect	-0.278	-0.402	-0.167	$p<0.001$

Note: We use a 95% confidence interval with a bootstrapping of 10,000

JSA). Specifically, CSE exerts an adverse indirect effect on JSA via AIA (Estimate = -0.072, 95% CI [-0.139, -0.036]) and AIL (Estimate = -0.040, 95% CI [-0.088, -0.012]), both significant at $p<0.001$. In addition, the chain mediation pathway (CSE → AIA → AIL → JSA) shows a significant adverse indirect effect (Estimate = -0.013, 95% CI [-0.040, -0.002], $p<0.001$). Finally, the total effect of CSE on JSA, considering these mediators, is -0.278 (95% CI [-0.402, -0.167], $p<0.001$), underscoring the substantial impact of CSE in reducing job selection anxiety through AIA and AIL.

In line with Baron and Kenny's conceptual steps and verified by the rigorous bootstrapping approach recommended by Baron and Kenny [91] and Preacher and Hayes [92], these results confirm that CSE exerts a significant chain mediation effect on JSA through AIA and AIL.

Discussion

This study aims to investigate CSE's impact on JSA among college students and further analyze the mediating roles of AIA and AIL. The survey results indicate that CSE has a significant adverse effect on JSA. This finding aligns with existing literature, which suggests that individuals with higher CSE exhibit greater confidence and lower anxiety when faced with career choices. This implies that CSE can help students alleviate JSA and enhance their confidence in career decision-making.

However, this study found that the direct effect of CSE on JSA became insignificant after introducing multiple mediator variables. This differs from the existing literature's conclusions that discuss CSE's direct impact on students' JSA. A possible reason is that AIA and AIL act as mediator variables, significantly moderating this process and weakening CSE's direct effect on JSA.

The results of the Bootstrap analysis showed that AIA and AIL played significant mediating roles in the relationship between CSE and JSA. Specifically, CSE significantly influenced AIA, which positively influenced AIL. This finding is consistent with the Technology Acceptance Model, indicating that a positive AIA can enhance students' AIL, thereby reducing JSA [66]. Additionally, the study found that AIL significantly negatively influenced JSA, further supporting the idea that improving AIL can help reduce students' anxiety during job-seeking.

Moreover, the chain mediation effect of CSE on JSA through AIA and AIL was significant. The results showed that CSE indirectly reduced JSA by enhancing students' AIA and increasing their AIL. This finding supports this study's hypothesis, indicating that complex interactions between CSE, AIA, and AIL influence students' JSA.

From the perspective of labour alienation theory, technological advancements can lead to the alienation of the labour process, causing workers to feel controlled by technology and thus develop ambivalent attitudes towards it [77]. This study found that high CSE can alleviate such ambivalent attitudes, making students more willing to accept and adapt to AI technology, thereby enhancing their AIL. This reduces the adverse effects of labour alienation and decreases JSA. These findings indicate that CSE can, to some extent, counteract the negative impacts of technological alienation, helping students maintain a positive mindset when facing the rapidly evolving technological environment. However, in an environment of labour alienation, maintaining high CSE requires greater attention and support to ensure that students can effectively cope with the challenges posed by technological changes.

Theoretical implications

Based on Marx's labour alienation theory, this study delves into the relationships among CSE, AIA, AIL, and JSA, providing theoretical insights and practical guidance. Labour alienation theory posits that with technological advancements, the labour process can become alienated, causing workers to feel controlled by technology and leading to ambivalent attitudes towards it. Within this theoretical framework, the study reveals the crucial role of high CSE in mitigating such ambivalent attitudes and adapting to technological changes.

First, the study confirms the significant role of CSE in alleviating the adverse effects of labour alienation. The data show that high CSE makes students more willing to accept and adapt to AI technology, enhancing their AIL and reducing JSA. This finding supports the labour alienation theory's hypothesis that technological advancement can make workers feel controlled [40, 85], but these negative impacts can be partially offset by enhancing CSE. High CSE boosts students' confidence in their abilities and improves their adaptability in a technology-driven environment.

Second, the study finds that AIA and AIL mediate between CSE and JSA. This finding broadens the application scope of labour alienation theory, indicating that technological attitudes and literacy are not only outcomes of the alienation process but also key factors in mitigating it. Specifically, positive AIA and high levels of AIL can help students better adapt to technological changes, reducing job-seeking anxiety caused by labour alienation.

Additionally, this study employs SEM and chain mediation effect analysis to elucidate the specific pathways through which CSE influences JSA via AIA and AIL. This analytical approach validates labour alienation theory's applicability in modern technological contexts and offers a novel theoretical framework to explain the mechanisms by which CSE functions during technological changes. This theoretical framework aids in a deeper understanding of how enhancing individuals' CSE, improving attitudes toward technology, and increasing AI literacy can alleviate JSA in a rapidly evolving technological landscape.

By uncovering the mechanisms through which CSE, AIA, and AIL mitigate JSA, this study provides the academic community with new perspectives and empirical support, offering valuable references for future research.

Practical implications

This study provides educators and policymakers with a roadmap to help university students better adapt to the job market in the era of AIA, alleviating JSA. First, the study highlights the importance of enhancing students' CSE [93, 94]. The findings indicate that high CSE alleviates students' ambivalent AIA and enhances their AIL, effectively reducing JSA caused by labour alienation. Educational institutions should prioritize curriculum and training programs that enhance students' CSE. Additionally, schools can offer more career planning and psychological counselling to improve students' CSE levels. For example, universities could implement mentorship programs connecting students with industry professionals, organize career development workshops with hands-on projects, and provide simulation exercises to build confidence in career decisions [95, 96]. Enhanced CSE will help students maintain a positive mindset and confidence in a rapidly changing technological environment.

Second, the study emphasizes the crucial role of AIA and AIL in mitigating JSA. Educators should help students develop a positive attitude toward AI, enabling them to accept better and adapt to technological changes. For instance, institutions could host regular AI-focused seminars featuring guest speakers from leading tech companies, organize interactive AI hackathons, and set up AI demonstration labs where students can engage directly with emerging technologies. Schools can conduct AI-related lectures, workshops, and practical activities to increase students' understanding and interest in AI technology. Moreover, curriculum design should focus on cultivating students' AIL, boosting their abilities and confidence in practical applications. These measures will help students face AI-induced challenges with more excellent composure and confidence, reducing JSA.

Finally, educational institutions and policymakers should focus on students' mental health and career development amidst technological advancements and labour alienation. Schools should provide comprehensive support systems, including psychological counselling, career guidance, and skills training, to help students cope with the pressures and uncertainties of technology. For example, establishing dedicated career centres that offer integrated services—such as AI literacy courses, stress management workshops, and tailored career transition programs—can provide the structured support needed to navigate a tech-driven labour market. By establishing a supportive learning and development environment, students will better adapt to changes in the labour market, enhance their career adaptability, and alleviate JSA.

Limitations, future research directions, and conclusions

Despite this study's theoretical and practical insights, several limitations must be acknowledged. Firstly, the sample limitation is a significant issue. The research data were collected from a limited sample of university students, which may restrict the generalizability of the findings. Students from different regions and backgrounds might exhibit varying levels of CSE, AIA, and AIL, thereby affecting their JSA differently. Secondly, the data were collected through self-reporting, which may involve social desirability bias or memory bias, potentially impacting the accuracy and reliability of the data [97]. Thirdly, the cross-sectional design of this study, while allowing for path analysis through SEM, should be complemented with longitudinal designs in future research to validate these relationships better. Fourth, this study focused on the impact of CSE, AIA, and AIL on JSA but did not consider other factors, such as family support and socioeconomic status, that might also influence JSA [98]. A significant limitation of the current study is that the sample comprises only Chinese university students. Although our findings offer important insights into the connections between career self-efficacy (CSE), attitude toward AI (AIA), and job-seeking anxiety (JSA) in this specific context, it is essential to exercise caution when attempting to generalize these results to other cultural environments or student groups.

Future research can expand and deepen this topic in several ways. Firstly, the impact of labour alienation on CSE can be explored as a cutting-edge topic, with potential mechanisms being investigated to understand this research finding better. Secondly, the sample scope can be broadened to include students from more regions and diverse backgrounds, thereby enhancing the generalizability and external validity of the findings. Thirdly, to better understand the long-term effects of CSE, AIA, and AIL on JSA, future research should employ longitudinal designs to track changes over different time points. Moreover, future studies could combine quantitative and qualitative methods, utilizing interviews and focus groups to gain deeper insights into students' views on CSE, AI technology, and its impact on JSA. More effort is needed to explore deeper mechanisms, especially within the framework of labour alienation theory. At the same time, future research should consider including more variables that may influence JSA, such as family background, social support, and personal traits, to comprehensively understand the formation mechanisms of JSA in the context of labour alienation. Lastly, future research should also aim to replicate and extend these findings by exploring similar relationships across different cultural contexts and demographic groups. Such research would enhance the generalizability of the current findings and provide a deeper understanding of how cultural factors can influence career development variables in an era of rapid technological change.

Conclusion

In summary, this study explores the relationships among CSE, AIA, AIL, and JSA in university students from the perspective of labour alienation theory. The results indicate that high CSE can mitigate the adverse effects of labour alienation, making students more willing to accept and adapt to AI technology, thereby enhancing their technical literacy and reducing JSA. AIA and AIL play significant mediating roles between CSE and JSA, further illustrating that enhancing individuals' CSE, improving their attitudes toward technology, and increasing their technical literacy can effectively reduce JSA in rapid technological advancement.

The findings of this study provide valuable references for educators and policymakers, emphasizing the importance of enhancing students' CSE and technical literacy. Furthermore, this study offers new perspectives and empirical support for applying labour alienation theory in modern technological environments. Although there are some limitations, the results provide valuable directions for future research, contributing to the ongoing exploration of how to better assist university students in adapting to and thriving in a rapidly changing job market.

Abbreviations

SEM	Structural Equation Modeling
AI	Artificial Intelligence
CSE	College Students' Career Self-efficacy
JSA	Job Search Anxiety
AIA	AI Attitudes
AIL	AI literacy

Acknowledgements
Thank all participants in this study and all members who helped with this study.

Author contributions
The authors contributed to this study as follows: Li ruihua was responsible for the study design, data collection, and drafting of the manuscript; Ouyang sha provided methodological guidance and reviewed the manuscript; Lin jianwei conducted data analysis, and served as the corresponding author. All authors have read and approved the final version of the manuscript.

Funding
The authors received no financial support for this article's research, authorship, and/or publication.

Data availability
The original contributions presented in the study are included in the article/ supplementary material, further inquiries can be directed to the corresponding author.

Declarations

Ethics approval and consent to participate
Informed consent was obtained from all individual participants included in the study. This study used an online questionnaire to collect data, and subjects could opt to complete the questionnaire at any time. This study was approved by the ethics committee of the Putian University (Approval Number: JCJY202402010047).

Consent for publication
Informed consent was obtained from all individual participants included in the study.

Competing interests
The authors declare no competing interests.

Received: 7 December 2024 / Accepted: 16 April 2025
Published online: 30 April 2025

References

1. China MoEotPsRo. The Class of 2025 is expected to graduate 12.22 million college graduates 2024 [Available from: http://www.moe.gov.cn/jyb_xwfb/s5147/202411/t20241115_1163118.html
2. Wang BC, Rau PLP, Yuan TY. Measuring user competence in using artificial intelligence: validity and reliability of artificial intelligence literacy scale. Behav Inf Technol. 2023;42(9):1324–37.
3. Yu J, Qi C. The impact of generative AI on employment and labor productivity. Rev Bus. 2023;44(1):53–67.
4. Kolade O, Owoseni A. Employment 5.0: the work of the future and the future of work. Technol Soc. 2022;71.
5. Tschang FT, Almirall E. Artificial intelligence as augmenting automation: implications for employment. Acad Manage Perspect. 2021;35(4):642–59.
6. Kramer B, Brynjolfsson E, McAfee A, Norton WW. The second machine age: work, progress, and prosperity in a time of brilliant technologies. Technovation. 2015;35:71.
7. Krasnov V. Marxism - philosophy and economics - sowell,t. Int J World Peace. 1988;5(3):166–9.
8. Jones P. Work without the worker: labour in the age of platform capitalism. Verso Books; 2021.
9. Healy M. Marx and Digital Machines. Marx and digital machines: Alienation, technology, capitalism. Critical, Digital and Social Media Studies; 2020. pp. 1-172.
10. Lin HZ, Chen Q. Artificial intelligence (AI) -integrated educational applications and college students' creativity and academic emotions: students and teachers' perceptions and attitudes. BMC Psychol. 2024;12(1).
11. Wang YM, Wei CL, Lin HH, Wang SC, Wang YS. What drives students' AI learning behavior: a perspective of AI anxiety. Interact Learn Environ. 2024;32(6):2584–600.
12. Gerlich M, Public Anxieties About AI. Implications for corporate strategy and societal impact. Administrative Sci. 2024;14(11).
13. Lent RW, Brown SD, Hackett G. Toward a unifying social cognitive theory of career and academic interest, choice, and performance. J Vocat Behav. 1994;45(1):79–122.

14. Lent RW, Hackett G. Career self-efficacy: empirical status and future directions. J Vocat Behav. 1987;30(3):347–82.
15. Sawitri DR, Creed PA. Adolescent-Parent career congruence as a predictor of job search preparatory behaviors: the role of proactivity. J Career Dev. 2022;49(1):60–75.
16. Razak N. How Self-Efficacy drives job performance: the role of job anxiety and intrinsic motivation. Jurnal Manajemen. 2021;25(2):190–205.
17. Lent RW, Morris TR, Wang RJ, Moturu BP, Cygrymus ER, Yeung JG. Test of a social cognitive model of proactive career behavior. J Career Assess. 2022;30(4):756–75.
18. Moore O, Livingston B, Susskind AM. Résumé screening heuristic outcomes: an examination of hiring manager evaluation Bias. Equality Divers Inclusion Int J. 2022;42(1):104–34.
19. Martínez N, Vinas A, Matute H. Examining potential gender Bias in Automated-Job alerts in the Spanish market. PLoS ONE. 2021;16(12):e0260409.
20. Dwivedi YK, Hughes L, Ismagilova E, Aarts G, Coombs C, Crick T et al. Artificial intelligence (AI): multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. Int J Inf Manage. 2021;57.
21. George AS. Artificial intelligence and the future of work: job shifting not job loss. Partners Univers Innovative Res Publication. 2024;2(2):17–37.
22. Baigi SFM, Sarbaz M, Ghaddaripouri K, Ghaddaripouri M, Mousavi AS, Kimiafar K. Attitudes, knowledge, and skills towards artificial intelligence among healthcare students: A systematic review. Health Sci Rep. 2023;6(3).
23. Bordot F. Artificial intelligence, robots and unemployment: evidence from Oecd countries. J Innov Econ Manage. 2022;37:117–38.
24. Xie J, Ruilin L, ChatGPT. Human alienation crisis and reflection caused by generative artificial intelligence. Chongqing Univ J Social Sci. 2023;29(5):111–24.
25. Zhao SY, Yi WC, Ye BJ, Zeng YD, Yang YF. The association between intolerance of uncertainty and Job-Seeking anxiety: A moderated mediation model. J Career Dev. 2024;51(1):106–24.
26. Kim J, Oh J, Rajaguru V. Job-Seeking anxiety and job Preparation behavior of undergraduate students. Healthcare. 2022;10(2).
27. Pandya SS, Wang J. Artificial intelligence in career development: a scoping review. Hum Resource Dev Int. 2024;27(3):324–44.
28. Hong H, Kim Y. Applying artificial intelligence in career education for students with intellectual disabilities: the effects on career self-efficacy and learning flow. Educ Inform Technol. 2024;29(18):25237–56.
29. Raja Mohan N. Leadership Skills in the AI-Driven Enterprise: Identifying New Competencies for Success and Humanities Conference. 2024;20(6s):1439-45.
30. Liang Y. The impact of artificial intelligence on employment and income distribution. J Educ Humanit Social Sci. 2024;27:166–71.
31. Xu M, Wang YW. Explainability increases trust resilience in intelligent agents. Br J Psychol. 2024. https://doi.org/10.1080/21598282.2024.2431466
32. Belle MA, Antwi CO, Ntim SY, Affum-Osei E, Ren J. Am I gonna get a job?? Graduating students' psychological capital, coping styles, and employment anxiety. J Career Dev. 2022;49(5):1122–36.
33. Liu BJ, Wei LW, Wu M, Luo TY. Speech production under uncertainty: how do job applicants experience and communicate with an AI interviewer? J Comput-Mediat Commun. 2023;28(4).
34. Chen W, Weicong C, Liang H, Suyu H, Yiwen W. Robots abide by ethical principles promote human-robot trust? The reverse effect of decision types and the human-robot projection hypothesis. Acta Physiol Sinica. 2024;56(2):194.
35. Bandura A. Self-efficacy mechanism in human agency. Am Psychol. 1982;37(2):122–47.
36. Bandura A. Self-efficacy - toward a unifying theory of behavioral change. Psychol Rev. 1977;84(2):191–215.
37. Bandura A, Barbaranelli C, Caprara GV, Pastorelli C. Self-efficacy beliefs as shapers of children's aspirations and career trajectories. Child Dev. 2001;72(1):187–206.
38. Lent RW, Brown SD, Larkin KC. Self-efficacy in the prediction of academic-performance and perceived career options. J Couns Psychol. 1986;33(3):265–9.
39. Corlett S, Stutterheim SE, Whiley LA. I only wanted one thing and that was to be who I am now: being a trans young adult and (re)negotiating vocational identity. Gend Work Organ. 2024;31(5):1786–811.
40. Ni JC, Zhang JW, Wang YM, Li DC, Chen CM. Relationship between career maturity, psychological separation, and occupational self-efficacy of postgraduates: moderating effect of registered residence type. BMC Psychol. 2023;11(1).
41. Salim RMA, Istiasih MR, Rumalutur NA, Situmorang DDB. The role of career decision self-efficacy as a mediator of peer support on students' career adaptability. Heliyon. 2023;9(4).
42. Bennett D, Knight E, Li I. The impact of pre-entry work experience on university students' perceived employability. J Furth High Educ. 2023;47(8):1140–54.
43. Lee GM, Shin HK. Effects of acceptance and commitment therapy on Job-Seeking stress, Self-Efficacy, experiential avoidance, depression, and anxiety. Korean J Stress Res. 2022;30(4):277–87.
44. Nwaogu JM, Chan APC. The impact of coping strategies and individual resilience on anxiety and depression among construction supervisors. Buildings. 2022;12(12):2148.
45. Zhao S, Yi W, Ye B, Zeng Y, Yang Y. The association between intolerance of uncertainty and Job-Seeking anxiety: A moderated mediation model. J Career Dev. 2023;51(1):106–24.
46. Deer LK, Gohn K, Kanaya T. Anxiety and Self-Efficacy as sequential mediators in US college students' career Preparation. Educ + Train. 2018;60(2):185–97.
47. Razak N. How Self-Efficacy drives job performance: the role of job anxiety and intrinsic motivation. Jurnal Manajemen. 2021;25(2):190.
48. Tojib D, Sujan R, Ma JZ, Tsarenko Y. How does service robot anthropomorphism affect human co-workers? J Service Manage. 2023;34(4):750–69.
49. Spektor F, Fox SE, Awumey E, Riordan CA, Rho HJ, Kulkarni C, et al. editors. Designing for Wellbeing: Worker-Generated Ideas on Adapting Algorithmic Management in the Hospitality Industry. ACM Designing Interactive Systems Conference (DIS) on Rebuilding and Resilience; 2023 Jul 10–14; Pittsburgh, PA2023.
50. Ramasamy R, Nithyanandan DV. Positive psychological factors of career development among undergraduate students. Int J Indian Psychol. 2016;3(4).
51. Van Ryn M, Vinokur AD. How did it work? An examination of the mechanisms through which an intervention for the unemployed promoted job-search behavior. Am J Community Psychol. 1992;20:577–97.
52. Bi Y, Mou S, Wang G, Liao M. The relationship between professional Self-Concept and career Decision-Making difficulties among postgraduate nursing students in China: the mediating role of career Decision-Making Self-Efficacy. Front Psychol. 2023;14.
53. Presbitero A, Teng-Calleja M. Job attitudes and career behaviors relating to employees' perceived incorporation of artificial intelligence in the workplace: a career self-management perspective. Personnel Rev. 2023;52(4):1169–87.
54. Shao C, Nah S, Makady H, McNealy J. Understanding User Attitudes Towards AI-Enabled Technologies: An Integrated Model of Self-Efficacy, TAM, and, Ethics AI. International Journal of Human–Computer Interaction. 2024:1–13.
55. Al-Bahrani M, Shindi YA, Al-Lawati SMAS, Bakkar B. A path analysis of effects of the career locus of control dimensions and career decision Self-Efficacy on career aspiration. Int J Adolescence Youth. 2021;26(1):367–75.
56. Sun Q. Self-Objectification and career aspirations among young Chinese women: the roles of Self-Esteem and career Decision-Making Self-Efficacy. Front Psychol. 2023;14.
57. Kong H, Jiang X, Zhou X, Baum T, Li J, Yu J. Influence of artificial intelligence (AI) perception on career resilience and informal learning. Tourism Rev. 2023;79(1):219–33.
58. Gerçek M. Serial multiple mediation of career adaptability and Self-Perceived employability in the relationship between career competencies and job search Self-Efficacy. High Educ Skills Work-Based Learn. 2023;14(2):461–78.
59. Kim J, Oh J, Rajaguru V, editors. Job-seeking anxiety and job Preparation behavior of undergraduate students. Healthcare: MDPI; 2022.
60. Lemay DJ, Basnet RB, Doleck T. Fearing the robot apocalypse: correlates of AI anxiety. Int J Learn Analytics Artif Intell Educ (Ijai). 2020;2(2):24.
61. Zhong YL, Xu F, Zhang LP. Influence of artificial intelligence applications on total factor productivity of enterprises-evidence from textual analysis of annual reports of Chinese-listed companies. Applied Economics. 2024;56(43):5205-23.
62. Yang GQ, Nie YM, Li HG, Wang HS. Digital transformation and low-carbon technology innovation in manufacturing firms: the mediating role of dynamic capabilities. Int J Prod Econ. 2023;263.
63. Restrepo P. Automation: theory, evidence, and outlook. Annual Rev Econ. 2023;16.
64. Liu GX, Ma CJ. Measuring EFL learners' use of ChatGPT in informal digital learning of english based on the technology acceptance model. Innov Lang Learn Teach. 2024;18(2):125–38.
65. Laupichler MC, Aster A, Raupach T. Delphi study for the development and preliminary validation of an item set for the assessment of non-experts' AI literacy. Computers and Education: Artificial Intelligence. 2023;4:100126.
66. Schiavo G, Businaro S, Zancanaro M. Comprehension, apprehension, and acceptance: Understanding the influence of literacy and anxiety on acceptance of artificial intelligence. Technol Soc. 2024;77.

67. Chang CC, Hwang GJ. ChatGPT-facilitated professional development: evidence from professional trainers' learning achievements, self-worth, and self-confidence. Interact Learn Environ. 2025;33(1):883–900.
68. Wieser M, Schoffmann K, Stefanics D, Bollin A, Pasterk S, editors. Investigating the Role of ChatGPT in Supporting Text-Based Programming Education for Students and Teachers. 16th International Conference on Informatics in Schools - Situation, Evolution, and Perspectives (ISSEP.); 2023 Oct 23–25; HEP Vaud, Univ Teacher Educ, Lausanne, SWITZERLAND2023.
69. Zhang X, and Yu M. The labor theory of value in the context of artificial intelligence: a historical and classical review. Int Crit Thought. 2024;14(4):519–49.
70. Salah M, Alhalbusi H, Ismail MM, Abdelfattah F. Chatting with ChatGPT: decoding the Mind of chatbot users and unveiling the intricate connections between user perception, trust and stereotype perception on self-esteem and psychological wellbeing. Curr Psychol. 2024;43(9):7843–58.
71. Hsu TC, Chang C, Lin YW. Effects of voice assistant creation using different learning approaches on performance of computational thinking. Comput Educ. 2023;192.
72. Algerafi MAM, Zhou YL, Alfadda H, Wijaya TT. Understanding the factors influencing higher education students' intention to adopt artificial Intelligence-Based robots. Ieee Access. 2023;11:99752–64.
73. Baron RM, Kenny DA. The moderator–mediator variable distinction in social psychological research: conceptual, strategic, and statistical considerations. J Personal Soc Psychol. 1986;51(6):1173–82.
74. Penn LT, Lent RW. The joint roles of career decision Self-Efficacy and personality traits in the prediction of career decidedness and decisional difficulty. J Career Assess. 2019;27(3):457–70.
75. Huang XX, Zhang J, Hudson L. Impact of math self-efficacy, math anxiety, and growth mindset on math and science career interest for middle school students: the gender moderating effect. Eur J Psychol Educ. 2019;34(3):621–40.
76. Schiavo G, Businaro S, Zancanaro M. Comprehension, apprehension, and acceptance: Understanding the influence of literacy and anxiety on acceptance of artificial intelligence. Technol Soc. 2024;77:102537.
77. Zhang M, Wang Q, Chen Y, He M, Zhou W, Yao Z et al. Internship and postgraduate entrance examination: A qualitative study on the psychological experience of undergraduate nursing students under dual pressure in China. Heliyon. 2024;10(17).
78. Byrne BM. Adaptation of assessment scales in cross-national research: issues, guidelines, and caveats. Int Perspect Psychol. 2016;5(1):51–65.
79. Kline RB. Principles and practice of structural equation modeling. Guilford; 2023.
80. Etikan I, Musa SA, Alkassim RS. Comparison of convenience sampling and purposive sampling. Am J Theoretical Appl Stat. 2016;5(1):1–4.
81. Goodboy AK, Kline RB. Statistical and practical concerns with published communication research featuring structural equation modeling. Communication Res Rep. 2017;34(1):68–77.
82. Hair JF, Risher JJ, Sarstedt M, Ringle CM. When to use and how to report the results of PLS-SEM. Eur Bus Rev. 2019;31(1):2–24.
83. Wang H, Jiao R. The relationship between career social support and career management competency: the mediating role of career decision-making self-efficacy. Curr Psychol. 2023;42(26):23018–27.
84. Schepman A, Rodway P. Initial validation of the general attitudes towards artificial intelligence scale. Computers Hum Behav Rep. 2020;1:100014.
85. Hwang HS, Zhu LC, Cui Q. Development and validation of a digital literacy scale in the artificial intelligence era for college students. KSII Trans Internet Inform Syst (TIIS). 2023;17(8):2241–58.
86. Yuzhu Z, Dewen Y. Trans-regional verifying and comparing research on vocational selection anxiety questionnaire of university graduate. Studies of Psychology and Behavior; 2011.
87. Kock N, Lynn GS. Lateral collinearity and misleading results in variance-based SEM: an illustration and recommendations. J Association Inform Syst. 2012;13(7):2.
88. Collier J. Applied structural equation modeling using AMOS: basic to advanced techniques. Routledge; 2020.
89. Henseler J, Ringle CM, Sarstedt M. A new criterion for assessing discriminant validity in variance-based structural equation modeling. J Acad Mark Sci. 2015;43:115–35.
90. Franke G, Sarstedt M. Heuristics versus statistics in discriminant validity testing: a comparison of four procedures. Internet Res. 2019;29(3):430–47.
91. Baron RM, Kenny DA. The moderator–mediator variable distinction in social psychological research: conceptual, strategic, and statistical considerations. J Personal Soc Psychol. 1986;51(6):1173.
92. Preacher KJ, Hayes AF. SPSS and SAS procedures for estimating indirect effects in simple mediation models. Behav Res Methods Instruments Computers. 2004;36:717–31.
93. van Hooft EAJ, Kammeyer-Mueller JD, Wanberg CR, Kanfer R, Basbug G. Job search and employment success: A quantitative review and future research agenda. J Appl Psychol. 2021;106(5):674–713.
94. Park S, Jeong S, Chai DS. Remote e-Workers' psychological wellbeing and career development in the era of COVID-19: challenges, success factors, and the roles of HRD professionals. Adv Developing Hum Resour. 2021;23(3):222–36.
95. Dai Y, Chai CS, Lin P-Y, Jong MSY, Guo Y. Jian-jun Q. Promoting students' wellbeing by developing their readiness for the artificial intelligence age. Sustainability. 2020;12(16):6597.
96. Du H, Sun Y, Jiang H, Islam AYMA, Gu X. Exploring the effects of AI literacy in teacher learning: an empirical study. Humanit Social Sci Commun. 2024;11(1).
97. Nederhof AJ. Methods of coping with social desirability bias: A review. Eur J Social Psychol. 1985;15(3):263–80.
98. Pisarik CT, Rowell PC, Thompson LK. A phenomenological study of career anxiety among college students. Career Dev Q. 2017;65(4):339–52.

Publisher's note

Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.