

Article

AI Literacy and Innovative Behaviour Among Chinese University Students in the Context of Sustainable Development in Higher Education: A Moderated Serial Mediation Model

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Abstract

Against the backdrop of growing attention to sustainable development in higher education, the widespread application of artificial intelligence (AI) technologies has made the relationship between university students' AI literacy and innovative behaviour an important issue. To examine this relationship and its underlying psychological mechanisms, this study developed a moderated serial mediation model based on the componential theory of creativity and conservation of resources theory. A questionnaire survey was conducted with 470 university students using measures of AI literacy, AI trust, AI self-efficacy, AI anxiety, and innovative behaviour. The results showed that: (1) AI literacy was significantly and positively associated with university students' innovative behaviour; (2) AI self-efficacy mediated this relationship, and AI trust and AI self-efficacy jointly formed a serial mediating pathway, whereas the independent mediating effect of AI trust was not significant; and (3) AI anxiety partially moderated the serial mediation model. This study contributes to a better understanding of the psychological mechanisms linking university students' AI literacy and innovative behaviour in the context of sustainable development in higher education. It also provides theoretical insights and empirical evidence for AI literacy education, student support services, and the cultivation of innovative capacity in universities.

Keywords: AI literacy; innovative behaviour; AI trust; AI self-efficacy; AI anxiety; college students



Academic Editor: Tai-Yi Yu

Received: 21 May 2026

Revised: 23 June 2026

Accepted: 30 June 2026

Published: 2 July 2026

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1. Introduction

Against the backdrop of increasing attention to sustainable development in higher education, cultivating university students with innovative capacity, digital adaptability, and the ability to solve complex problems has become an important task for universities. Sustainable development in higher education is not only concerned with the continuous improvement of educational resources and institutional systems, but also emphasises the development of students' future-oriented competencies. UNESCO's states that education should help learners understand complex issues, make responsible decisions, and develop the capacity to participate in social transformation [1]. In the Chinese context, the also calls for improving mechanisms for identifying and cultivating top innovative talent, with a

particular focus on strengthening students' innovative capacity [2]. Therefore, university students' innovative behaviour (IB) is not only related to the effectiveness of innovation and entrepreneurship education in universities, but also closely linked to the sustainable capacity of higher education to serve social development and cultivate future talent.

IB refers to the behavioural process through which individuals proactively generate, promote, and implement new ideas, methods, or solutions [3]. Among university students, innovative behaviour is reflected not only in the generation of new ideas, but also in students' active experimentation with and application of new technologies, resources, and methods in learning, research training, social practice, and problem-solving. Previous research has explained university students' innovative behaviour from three main perspectives. First, in terms of individual characteristics, factors such as learning motivation, self-confidence, and learning engagement are closely related to students' creativity or innovative behaviour [4,5]. Second, in terms of the educational environment, external support such as an innovative climate, teacher support, and problem-solving training may help students propose, refine, and implement new ideas [6]. Third, in terms of learning resources and technological contexts, collaborative learning, knowledge sharing, and information literacy activities have also been found to be associated with students' innovative tendencies or related learning outcomes [7]. These studies provide an important basis for understanding university students' innovative behaviour. However, their explanatory frameworks are largely grounded in traditional educational environments or general digital learning contexts. As AI technologies are increasingly integrated into higher education, the technological environment in which students engage in innovative practices is changing. It is therefore necessary to further examine the relationships among students' technological understanding, resource use, and innovative behaviour in AI-enabled learning contexts [8].

Artificial intelligence literacy (AIL) provides an important entry point for understanding university students' innovative behaviour in AI-enabled learning contexts. Previous studies have generally defined AIL as an individual's integrated capacity to understand, evaluate, communicate with, and effectively use AI technologies [9,10]. In AI-enabled learning contexts, AIL is not only related to whether students can use AI tools, but also to whether they can judge technological boundaries, identify potential risks, and use AI as a supportive resource in innovative practice. Prior research has also emphasised that students need to become responsible users and co-creators of AI in order to adapt to future demands in learning, work, and social development [11]. From the perspective of the componential theory of creativity, innovative behaviour depends on domain-relevant skills, creativity-relevant processes, and task motivation [12]. Accordingly, AIL can be understood as an important competence base that supports university students' engagement in innovative practice within AI-enabled learning contexts. However, the relationship between AIL and innovative behaviour may not be merely direct. Even when students possess some understanding of AI and the ability to apply it, their further engagement in innovative exploration during learning, research training, and practical tasks may depend on several psychological factors. These include whether they are willing to accept AI tools, whether they believe they can use AI effectively to complete tasks, and what kinds of emotional experiences they have when interacting with AI. Existing studies have paid greater attention to AI tool use, technology acceptance intentions, and digital learning performance. However, there is still insufficient explanation of how these psychological processes are involved in the association between AIL and university students' innovative behaviour [13,14]. Conservation of resources theory suggests that individuals tend to acquire, preserve, and mobilise valuable resources when facing task demands and environmental changes [15]. In the context of this study, AI trust (AIT) and AI self-efficacy (AISE) can be understood as important psychological resources that support university

students' participation in AI-enabled innovative practice. By contrast, AI anxiety (AIA) may shape the strength of the associations among these psychological resources and innovative behaviour.

Drawing on the above theoretical background, this study develops a moderated serial mediation model to examine the relationship between university students' artificial intelligence literacy and innovative behaviour in the context of sustainable development in higher education. It further analyses the roles of AI trust, AI self-efficacy, and AI anxiety in this relationship. Specifically, this study addresses three questions: first, whether AI literacy is significantly associated with university students' innovative behaviour; second, whether AI trust and AI self-efficacy form a psychological pathway linking AI literacy to innovative behaviour; and third, whether AI anxiety serves as a boundary condition in this process.

2. Literature Review

2.1. *The Relationship Between AIL and IB*

As an integrated capacity to understand, evaluate, use, and appropriately respond to AI technologies, artificial intelligence literacy involves not only technical knowledge and tool operation, but also critical judgement of AI-generated outputs, ethical awareness, and problem-solving ability [10,16,17]. Therefore, AIL is not merely the ability to use tools. Rather, it represents an important competence base through which individuals can transform AI technologies into supportive resources for learning, problem-solving, and innovation. From the perspective of the componential theory of creativity, IB is closely related to domain-relevant skills, creativity-relevant skills, and task motivation [18]. In contexts where AI tools are used for learning and problem-solving, AIL can be regarded as an emerging form of domain-relevant skill.

University students with higher levels of AIL are more likely to understand the functional boundaries and appropriate conditions of AI tools. They may also be better able to use AI for information retrieval, idea generation, solution comparison, and content optimisation in learning and practical tasks [14]. In addition, the critical evaluation and ethical use capacities embedded in AIL may help students verify, filter, and reprocess AI-generated content. This can reduce mechanical reliance on AI outputs and make AI tools more likely to function as supportive resources in the innovation process, rather than as technological substitutes for individual thinking [19]. Previous research further suggests that the relationship between AI tools and individual creative performance does not emerge automatically. Instead, it is closely related to users' ability to understand, evaluate, and reprocess AI-generated outputs [20]. Accordingly, university students with higher levels of AIL may be more likely to transform AI technologies into resources that support innovation and to demonstrate higher levels of IB in learning and practice. Therefore, this study proposes the following hypothesis:

H1. *There is a positive relationship between AIL and university students' IB.*

2.2. *AIT as a Mediator of the AIL-IB Relationship*

AIT refers to individuals' positive expectations regarding the capability, reliability, predictability, and controllability of risks associated with an AI system during their interaction with it [21]. However, when university students use AI for learning, research training, and innovative practice, AIT does not equate to the unconditional acceptance of AI-generated outputs. According to the perspective of trust calibration, individuals' trust in automated systems should be based on an understanding of the system's purpose, operating processes, and actual performance; insufficient trust may lead to technology

disuse, whereas excessive trust may result in blind reliance [22]. Previous research has also shown that trust in automation is shaped by multiple factors, including individual characteristics, contextual conditions, and system-related experience. Users' understanding of system performance, operational features, and usage contexts may influence the formation of trust [23]. Accordingly, university students with higher levels of AIL are more likely to understand the scope of application, functional boundaries, and potential limitations of AI tools. They may also be better able to judge the reliability and applicability of AI-generated content. Such understanding and judgement may help reduce uncertainty in human–AI interaction and enable students to develop relatively rational and appropriately calibrated AIT.

AIT may further be involved in the formation of university students' IB. IB is typically exploratory and uncertain. When students propose new ideas, experiment with new tools, integrate new resources, or promote new solutions, they often face risks such as failure, inefficiency, or uncontrollable outcomes [24]. In this process, AI can serve as an external cognitive support tool that facilitates problem identification, information integration, idea expansion, and solution iteration. However, whether such support is incorporated into actual innovative activities depends not only on the functional advantages of AI tools themselves, but also on whether students perceive these tools as usable, reliable, and associated with controllable risks. Previous studies have shown that trust is an important psychological basis for individuals' acceptance and use of AI, and is closely related to behavioural intention, willingness to use, and actual use behaviour [13]. In educational contexts, students' trust in AI-based educational technologies is also associated with their readiness to adopt and willingness to use such technologies. This further suggests that university students' trust judgements regarding AI tools may be closely related to their willingness to incorporate AI into learning and innovation tasks [25]. On this basis, AIL may help university students develop appropriately calibrated AIT, making them more willing to use AI as an external cognitive resource for problem identification, information integration, idea generation, and solution iteration. In turn, AIL may be indirectly associated with IB through AIT. Therefore, this study proposes the following hypothesis:

H2. *AIT mediates the relationship between AIL and university students' IB.*

2.3. AISE as a Mediator of the AIL-IB Relationship

AISE refers to individuals' beliefs in their ability to effectively understand, operate, and apply AI technologies to complete relevant tasks [26]. Compared with general self-efficacy, AISE is more strongly embedded in technology-specific contexts and human–AI interaction. It involves not only individuals' judgements about their own technical operational ability, but also their confidence in obtaining support from AI, understanding AI-generated outputs, and completing tasks with the assistance of AI. Self-efficacy theory suggests that individuals' capability beliefs are generally derived from prior experience, perceived competence, and task contexts, and that these beliefs shape subsequent task choices, effort, and sustained engagement [27]. In the context of AI use, university students with higher levels of AIL are usually more familiar with the basic logic, modes of operation, and boundaries of application of AI tools. They may also be better able to select tools, design prompts, evaluate outputs, revise results, and iterate tasks according to task requirements. Such knowledge and usage experience may strengthen individuals' sense of control over AI-related tasks, making them more likely to develop a positive capability expectation that they can use AI effectively to complete tasks. Existing research on AIL courses for university students has also shown that systematic AI knowledge learning and practical experience are associated with improvements in students' conceptual understanding of AI,

self-perceived AIL, and sense of AI empowerment [28]. Accordingly, university students with higher levels of AIL may be more likely to develop stronger AISE through the processes of understanding, using, and evaluating AI.

AISE may further be associated with university students' IB. Innovative activities are often accompanied by task uncertainty, repeated trial and error, and solution iteration. Whether individuals believe that they can effectively mobilise resources and complete relevant tasks may shape their active engagement and sustained exploration in the innovation process. Previous studies have shown that creative self-efficacy is closely related to individuals' creative performance and IB. Tierney and Farmer proposed the construct of creative self-efficacy and found that it was associated with individual creative performance [29]. Haase et al., based on a meta-analysis of 41 studies and 60 effect sizes, also showed a moderate correlation between creative self-efficacy and creativity [30]. Newman et al. further found, in an organisational context, that creative self-efficacy was associated with employees' innovative behaviour [31]. From this perspective, AISE can be understood as a capability belief specific to the context of AI use. University students with higher levels of AISE may be more likely to believe that they can effectively mobilise AI resources, understand and revise AI-generated outputs, and transform them into adjustable and implementable solutions. As a result, they may be more willing to use AI in idea generation, solution optimisation, and practical application. It can therefore be inferred that AISE may mediate the association between AIL and university students' IB. Accordingly, this study proposes the following hypothesis:

H3. *AISE mediates the relationship between AIL and university students' IB.*

2.4. AIT and AISE as Sequential Mediators of the AIL-IB Relationship

According to the conservation of resources theory, individuals' existing resources may create conditions for the acquisition of subsequent resources, thereby forming a resource gain process [15]. On this basis, AIL may not only be associated with AIT and AISE separately, but may also be related to university students' IB through their sequential effects. University students with higher levels of AIL are more likely to develop relatively rational and appropriately calibrated AIT based on their understanding of the functional boundaries, applicable conditions, and potential risks of AI tools. Existing research on AIT has suggested that individuals' trust judgements regarding the capability, reliability, and explainability of AI systems are an important prerequisite for their acceptance and use of AI technologies [32]. However, AIT does not necessarily translate directly into AISE. AIT primarily reflects university students' evaluative judgements about whether AI tools are reliable, usable, and associated with controllable risks. Only when such trust is further reflected in sustained exposure, task attempts, and reflective use can it provide an experiential basis for the development of AISE. Research on technology self-efficacy has also shown that individuals' judgements about their own ability to use technology are closely related to prior usage experience, task familiarity, and use-related feedback [33]. Therefore, when university students regard AI as a relatively trustworthy external support resource and continue to accumulate usage experience and task feedback in learning and innovation tasks, their judgements about their ability to use AI effectively to complete tasks may be strengthened. Furthermore, higher AISE may make students more confident in their ability to understand, revise, and integrate AI-generated outputs, and to apply them to problem identification, idea generation, solution optimisation, and practical exploration. It can therefore be inferred that AIL may be indirectly associated with university students' IB through the sequential mediating pathway of AIT and AISE. Accordingly, this study proposes the following hypothesis:

H4. *AIT and AISE play a chain mediating role between AIL and university students' IB.*

2.5. AIA as a Moderator

AIA refers to the tension, worry, fear, or unease that individuals experience when facing AI technologies. It may arise not only from concerns about the difficulty of learning to use AI tools, but also from worries about technological replacement, algorithmic opacity, and potential risks [34]. In higher education contexts, university students' AIA is often reflected in concerns about the learning costs of AI, capability gaps, future competitive pressure, and the uncertainty of AI-generated outputs.

According to the cognitive appraisal theory of stress, when individuals encounter stressors, they evaluate them as either threats or challenges by considering their own resources and situational demands, and then develop different coping responses accordingly [35]. Therefore, AIA should not be simply understood as a unidimensional negative emotion. Research on challenge and hindrance stressors suggests that the behavioural consequences of stressors can be dual in nature. When stress is appraised as a hindrance, individuals are more likely to show avoidance, withdrawal, or inefficient coping. When stress is appraised as a challenge, it may be associated with higher motivation, engagement, and adaptive action [36,37]. Recent research in AI-related contexts has provided similar evidence. Wang found that AI learning anxiety was negatively associated with students' learning motivation, whereas AI job replacement anxiety could be positively associated with extrinsic learning motivation and willingness to learn AI [38]. Chang further suggested that AI-driven challenge technostress may be associated with AI adoption intention through positive emotions, whereas hindrance technostress may be related to lower adoption intention through AIA [39].

These findings suggest that the role of AIA may depend on the competence resources and psychological resources available to university students. When students lack AIL, AIT, or AISE, AIA may be more likely to be experienced as a threat and may be associated with avoidance or inefficient use of AI tools. By contrast, when students already possess a certain level of AIL, AIT, or AISE, moderate AIA may reflect sensitivity to technological change, capability gaps, and innovation-related pressure, and may be associated with greater attention to, mobilisation of, and integration of AI resources. Accordingly, this study regards AIA as an emotional boundary condition in the relationships among AIL, AIT, AISE, and IB, and proposes that it may moderate the strength of the relevant paths in the model. Therefore, this study proposes the following hypotheses:

H5a. *AIA moderates the relationship between AIL and AIT.*

H5b. *AIA moderates the relationship between AIL and AISE.*

H5c. *AIA moderates the direct relationship between AIL and university students' IB.*

H5d. *AIA moderates the relationship between AIT and university students' IB.*

H5e. *AIA moderates the relationship between AIT and AISE.*

H5f. *AIA moderates the relationship between AISE and university students' IB.*

In summary, drawing on the componential theory of creativity, conservation of resources theory, and cognitive appraisal theory of stress, this study constructs a moderated serial mediation model to examine the relationship between AIL and university students' IB. Specifically, this study tests whether AIT and AISE play a serial mediating role in

this relationship, and further examines whether AIA serves as a boundary condition that moderates the strength of the relevant paths. The research model is presented in Figure 1.

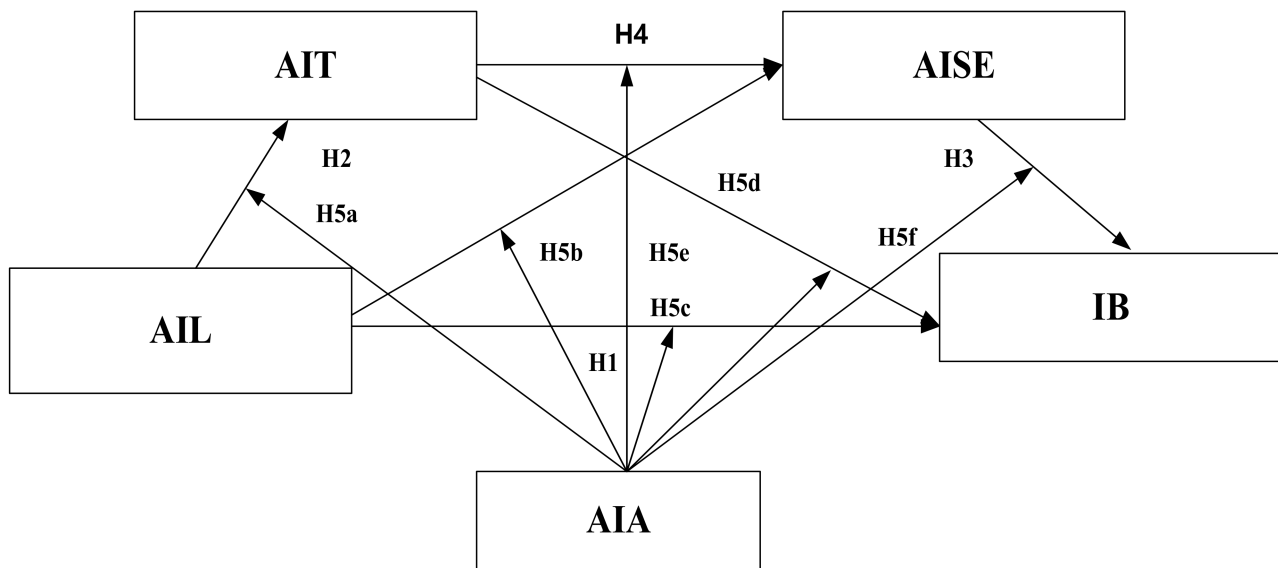


Figure 1. The proposed moderated chain mediation model. Note: AIL = artificial intelligence literacy; AIT = AI trust; AISE = AI self-efficacy; IB = innovative behaviour; AIA = AI anxiety. The same applies below.

3. Methods

3.1. Participants

This study used convenience sampling and recruited university students from universities in central China as participants. Data were collected between 1 April and 25 April 2026. After obtaining permission from the university and course instructors, the researchers administered the survey collectively during students' self-study periods. The questionnaire was distributed online through the Wenjuanxing platform, and participants completed it on site using mobile phones or other electronic devices. Before the survey, the researchers explained the purpose of the study, the principle of anonymity, the use of the data, the voluntary nature of participation, and participants' right to withdraw at any time. Participants proceeded to the formal questionnaire only after reading and confirming the informed consent information. The questionnaire was completed anonymously, with an average completion time of approximately 8 min. After completing the questionnaire, participants received a pen as a token of appreciation.

A total of 513 questionnaires were distributed. To ensure data quality, attention-check items were included in the questionnaire, such as "Please select option D for this item". Questionnaires were deemed invalid if participants failed to answer the attention-check items as required, showed obvious patterned responses, or did not meet the study requirements. Ultimately, 470 valid questionnaires were obtained, yielding a valid response rate of 91.62%. Among the valid sample, 96 participants were male, accounting for 20.4%, and 374 were female, accounting for 79.6%. The mean age of the participants was 20.31 years, with a standard deviation of 2.06. In terms of disciplinary background, 47.56% were from humanities-related majors, 29.43% from social science majors, 21.25% from science and engineering majors, and 1.75% from other majors. This study was approved by the Ethics Committee of Zhengzhou Shengda University, with approval granted on 20 March 2026. All participants took part in the survey voluntarily and anonymously, and provided informed consent. Participants were allowed to withdraw from the survey at

any point without any adverse consequences. The questionnaire data were used solely for academic research and were analysed statistically in anonymised form.

3.2. Research Instruments

The scales used in this study were mainly drawn from established measurement instruments, with priority given to scales that had been developed, revised, or previously used in Chinese or China-based contexts. For scales originally developed in English or applied in contexts that differed from the present study, bilingual researchers with relevant research backgrounds were invited to conduct translation and back-translation. Researchers in educational psychology and AI education were then invited to review the items in terms of semantic consistency, cultural appropriateness, and contextual fit. On this basis, necessary adjustments were made to the measurement objects, application scenarios, and wording of some items in light of the AI use context and the characteristics of Chinese university students. These adjustments did not alter the core constructs measured by the scales. Subsequently, Cronbach's α coefficients and confirmatory factor analysis were used to examine the reliability and structural validity of each scale in the present sample.

3.2.1. AIL Scale

AIL was measured using the University Students' Artificial Intelligence Literacy Scale developed by Zhou et al. [40]. The scale consists of 15 items and includes four dimensions: technological cognition, tool application, innovative practice, and ethical responsibility. Sample items include "I can rationally analyse the potential impact of GAI on industrial transformation and educational models" for technological cognition, "I can proficiently operate at least one GAI tool for content generation" for tool application, "I can use GAI as a creative partner to generate original content" for innovative practice, and "I can clearly distinguish the boundary between AI assistance and academic misconduct" for ethical responsibility. The scale uses a 5-point Likert response format ranging from 1 = strongly disagree to 5 = strongly agree, with higher scores indicating higher levels of AIL. In the present study, the overall Cronbach's α coefficient of the scale was 0.924, and the α coefficients for the four dimensions were 0.847, 0.863, 0.878, and 0.865, respectively. The results of confirmatory factor analysis indicated that the measurement model fitted the data well: $\chi^2/df = 3.97$, CFI = 0.943, TLI = 0.929, RMSEA = 0.080, and SRMR = 0.061. These results suggest that the scale demonstrated good reliability and structural validity in the present sample.

3.2.2. IB Scale

IB was measured using the Innovative Behaviour Scale developed by Scott and Bruce [41]. The scale is a unidimensional measure consisting of six items, covering idea generation, idea promotion, and plan implementation. A representative item is "In learning or practical tasks, I usually actively seek to apply new processes, technologies, and methods". The scale uses a 5-point Likert response format ranging from 1 = never to 5 = always, with higher scores indicating higher levels of IB. Previous studies have used related measures of IB with Chinese university student samples and have shown good applicability [42]. In the present study, the Cronbach's α coefficient of the scale was 0.911. The results of confirmatory factor analysis indicated that the single-factor measurement model fitted the data well: $\chi^2/df = 3.65$, CFI = 0.989, TLI = 0.977, RMSEA = 0.075, and SRMR = 0.018. These results suggest that the scale demonstrated good reliability and structural validity in the present sample.

3.2.3. AIT Scale

AIT was measured using the trust dimension of the Social Service Robot Interaction Trust Scale developed by Chi et al. [43]. In line with the context of the present study, this dimension was used to assess university students' general trust in AI tools. The dimension consists of three items. A representative item is "I would usually trust AI until it gives me a reason not to trust it". The scale uses a 7-point Likert response format, with higher scores indicating higher levels of AIT. There are sufficient theoretical and methodological grounds for the contextual adaptation of this trust dimension in the present study. The original scale was designed to measure individuals' trust during interactions with artificially intelligent social robots, and its trust dimension primarily captures individuals' overall evaluations of intelligent systems' competence, reliability, and risk controllability, rather than evaluations of social robots' appearance, embodied form, or physical interaction features. Therefore, the core conceptual meaning of this dimension is highly consistent with the AIT construct examined in the present study. In its application, this study did not directly adopt the original items; instead, while retaining the core meaning of the trust construct, it appropriately adapted the measurement object and item wording in accordance with the Chinese university student sample and the context of AI tool use in learning- and innovation-related activities. Meanwhile, previous research has applied this trust dimension in AI acceptance research among Chinese university students and verified its good applicability [44]. In the present study, the Cronbach's α coefficient of the scale was 0.865. The results of confirmatory factor analysis showed that the standardised factor loadings of all items ranged from 0.773 to 0.879, and all were statistically significant ($p < 0.001$). As the scale contains only three observed indicators, the single-factor measurement model was just-identified; therefore, model fit indices were not used as the primary basis for evaluation. Overall, the scale demonstrated good reliability and structural validity in the present sample.

3.2.4. AISE Scale

AISE was measured using the AI Self-Efficacy Scale developed by Wang and Chuang [45]. The scale consists of 22 items and includes four dimensions: assistance, anthropomorphic interaction, comfort with AI, and technological skills. Sample items include "AI technologies/products are good assistants for learning" for assistance, "I think the tone of AI technologies/products during interaction is the same as that of real people" for anthropomorphic interaction, "I feel comfortable when interacting with AI technologies/products" for comfort with AI, and "When using AI technologies/products, I am not worried about damaging them by pressing the wrong button" for technological skills. The scale uses a 7-point Likert response format ranging from 1 = strongly disagree to 7 = strongly agree, with higher scores indicating stronger AISE. The scale has been used in the Chinese higher education context with a sample of undergraduate students majoring in special education, and has shown good applicability [46]. In the present study, the overall Cronbach's α coefficient of the scale was 0.948, and the α coefficients for the four dimensions were 0.923, 0.934, 0.916, and 0.881, respectively. Given the relatively large number of items and the multidimensional structure of the scale, this study adopted dimension parcelling and used the mean scores of the four dimensions as observed indicators in confirmatory factor analysis. The results showed good model fit: $\chi^2/df = 1.44$, CFI = 0.999, TLI = 0.997, RMSEA = 0.031, and SRMR = 0.008. These results suggest that the scale demonstrated good reliability and structural validity in the present sample.

3.2.5. AIA Scale

AIA was measured using the Artificial Intelligence Anxiety Scale (AIAS) developed by Wang and Wang [47]. The scale consists of 21 items and includes four dimensions: learning anxiety, job replacement anxiety, socio-technical blindness anxiety, and AI configuration anxiety. Sample items include “Learning to use AI technologies or products makes me feel anxious” for learning anxiety, “I am worried that AI technologies or products may replace human beings” for job replacement anxiety, “I am worried that AI technologies or products may get out of control and malfunction” for socio-technical blindness anxiety, and “I find humanoid AI technologies or products frightening” for AI configuration anxiety. The scale uses a 7-point Likert response format ranging from 1 = strongly disagree to 7 = strongly agree, with higher scores indicating higher levels of AIA. Previous studies have used related measures of AIA with Chinese undergraduate samples and have shown good applicability in higher education contexts [26]. In the present study, the overall Cronbach’s α coefficient of the scale was 0.952, and the α coefficients for the four dimensions were 0.936, 0.918, 0.914, and 0.922, respectively. Given the relatively large number of items and the multidimensional structure of the scale, this study adopted dimension parcelling and used the mean scores of the four dimensions as observed indicators in confirmatory factor analysis. The results showed good model fit: $\chi^2/df = 1.78$, CFI = 0.998, TLI = 0.995, RMSEA = 0.041, and SRMR = 0.009. These results suggest that the scale demonstrated good reliability and structural validity in the present sample.

3.3. Research Procedures

This study used SPSS 26.0 and Mplus 8.3 for data analysis. First, SPSS was used to conduct descriptive statistics, reliability analysis, Pearson correlation analysis, and common method bias tests. Second, Mplus 8.3 was used to conduct confirmatory factor analysis and structural equation modelling to examine the serial mediating effects among AIL, AIT, AISE, and IB. Finally, PROCESS Model 92 was used to test the moderating effect of AIA and the moderated serial mediation effect, and the bootstrap method was used to estimate confidence intervals for the indirect effects.

In the model testing, gender and age were included as control variables. These two variables are commonly used basic demographic variables in studies of university student samples and can help control for potential interference arising from individual background differences. Given that the selection of control variables should be clearly justified, and that too many control variables should not be mechanically included so as to avoid overcontrol [48], this study included only gender and age as basic control variables. Variables such as digital literacy, AI use experience, and prior AI knowledge may conceptually overlap with AIL, and future research may further examine their supplementary roles.

4. Results

4.1. Common Method Bias

Given that all core variables in this study were measured using self-report questionnaires, there was a potential risk of common method bias. To reduce its possible influence, several procedural remedies were adopted, including anonymous responses, voluntary participation, the right to withdraw at any time, an emphasis that there were no right or wrong answers, adjustment of the presentation order of items from different scales, and the inclusion of attention-check items. In terms of statistical testing, Harman’s single-factor test was first conducted. The results of the unrotated exploratory factor analysis showed that 11 common factors had eigenvalues greater than 1, and that the first common factor explained 26.41% of the variance, which was below the 40% threshold criterion [49]. This suggests that a single factor did not account for most of the measurement variance.

To further enhance the robustness of the assessment, this study also used the full-collinearity variance inflation factor (VIF) method. Specifically, each of the five core variables was treated in turn as the dependent variable, while the remaining variables were entered as predictors in regression analyses. The results showed that all VIF values were below 3.3, with the maximum VIF being 1.760, indicating that common method bias was unlikely to pose a serious threat to the findings. In addition, the unmeasured latent method factor approach was used for further examination. Given that some scales contained a relatively large number of items and had multidimensional structures, this study added an unmeasured latent method factor to the five-factor measurement model based on item parcelling. The results showed that the parcelled five-factor model fitted the data well: $\chi^2 = 164.353$, $df = 94$, CFI = 0.992, TLI = 0.989, RMSEA = 0.040, and SRMR = 0.019. After adding the method factor, the model fit was as follows: $\chi^2 = 88.195$, $df = 78$, CFI = 0.999, TLI = 0.998, RMSEA = 0.017, and SRMR = 0.013. Although model fit improved after the inclusion of the method factor, the results of the procedural controls, Harman's single-factor test, the full-collinearity VIF test, and the unmeasured latent method factor test collectively suggest that serious common method bias was not present in the data.

4.2. Descriptive Statistics and Correlation Analysis

The descriptive statistics results (Table 1) show that the mean scores of the participants on the core constructs of AIL, AIT, AISE, IB, and AIA were all at an upper-middle level, indicating that while the surveyed cohort of university students exhibited relatively good cognitive understanding and efficacy beliefs regarding artificial intelligence technology, they were also accompanied by a certain degree of perceived technological anxiety. The results of the Pearson correlation test revealed that there were significant positive correlations pairwise among AIL, AIT, AISE, IB, and AIA. Regarding demographic control variables, apart from gender showing a significant negative correlation with AISE, age did not exhibit any statistically significant associations with the various core variables.

Table 1. Means, Standard Deviations, and Correlations.

Variable	1	2	3	4	5	6	7
1. Gender	1						
2. Age	0.030	1					
3. AIL	−0.043	−0.010	1				
4. AIT	−0.036	0.045	0.173 ***	1			
5. AISE	−0.141 **	0.030	0.363 ***	0.557 ***	1		
6. IB	−0.040	0.011	0.396 ***	0.237 ***	0.426 ***	1	
7. AIA	−0.010	−0.041	0.115 *	0.350 ***	0.359 ***	0.230 ***	1
M	−	20.31	3.377	4.269	4.564	3.292	4.177
SD	−	2.060	0.613	1.008	0.758	0.602	0.918

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. 0 = male, 1 = female; the same applies below.

4.3. Analysis of the Chain Mediating Effect of AIT and AISE

To test the research hypotheses, this study constructed a structural equation modelling (SEM) model using Mplus 8.3 after controlling for participants' age and gender. A bias-corrected non-parametric percentile bootstrap method with 5000 resamples was used to examine the serial mediating effects of AIT and AISE in the relationship between AIL and IB. The results showed that the structural model fitted the data well: $\chi^2/df = 2.959$, RMSEA = 0.065, CFI = 0.963, TLI = 0.941, and SRMR = 0.036, indicating good model–data fit. After confirming the acceptable model fit, this study further examined the path relationships among the main latent variables. The standardised path coefficients showed that AIL was significantly and positively associated with university students' IB ($\beta = 0.182$, $p < 0.001$),

supporting H1. AIL was also significantly and positively associated with AIT ($\beta = 0.196$, $p < 0.001$) and AISE ($\beta = 0.325$, $p < 0.001$). In addition, AIT was significantly and positively associated with AISE ($\beta = 0.492$, $p < 0.001$), and AISE was significantly and positively associated with IB ($\beta = 0.194$, $p < 0.001$). By contrast, the direct path from AIT to IB was not significant ($\beta = -0.003$, $p = 0.932$), suggesting that the direct association between AIT and IB was not supported in this model.

The bootstrap test of indirect effects further showed that the total indirect effect of AIL on IB was significant (Estimate = 0.167, 95% CI [0.086, 0.278]; see Table 2). Specifically, the indirect path from AIL to IB through AIT was not significant (Estimate = -0.003 , 95% CI [-0.034 , 0.029]); therefore, H2 was not supported. The indirect path from AIL to IB through AISE was significant (Estimate = 0.130, 95% CI [0.059, 0.233]), supporting H3. Furthermore, the serial indirect path from AIL to IB through AIT and AISE was also significant (Estimate = 0.040, 95% CI [0.014, 0.089]), supporting H4. These results indicate that AIL was not only directly associated with university students' IB but also indirectly associated with IB through AISE and through the serial pathway of AIT and AISE.

Table 2. Mediating effect analysis.

Path	Effect	BootSE	95% CI	
			LLCI	ULCI
Total effect	0.529	0.080	0.386	0.703
Direct effect	0.303	0.065	0.169	0.421
Indirect effect	0.167	0.048	0.086	0.278
Indirect effect 1	-0.003	0.015	-0.034	0.029
Indirect effect 2	0.130	0.044	0.059	0.233
Indirect effect 3	0.040	0.018	0.014	0.089

To examine the robustness of the serial mediation results, this study further conducted a supplementary analysis using SPSS PROCESS Model 6 based on the mean scores of the variables, while controlling for gender and age. The results showed that the significance pattern obtained from the PROCESS analysis was largely consistent with the Mplus SEM results. The simple indirect path from AIL to IB through AIT was not significant (Effect = 0.002, 95% CI [-0.016 , 0.027]), whereas the indirect path from AIL to IB through AISE was significant (Effect = 0.087, 95% CI [0.041, 0.138]). The serial indirect path from AIL to IB through AIT and AISE was also significant (Effect = 0.028, 95% CI [0.009, 0.053]). These findings further indicate that the independent indirect path through AIT was not supported, whereas the AISE pathway and the serial pathway of AIT–AISE showed good stability.

To further examine the robustness of the mediator ordering proposed in the theoretical model, this study conducted a supplementary alternative serial mediation analysis using PROCESS Model 6, in which the order of the two mediators was reversed. Specifically, after controlling for gender and age, AISE was specified as the first mediator and AIT as the second mediator to test the alternative pathway through which AIL was associated with IB via AISE and AIT. The results showed that AIL significantly and positively predicted AISE ($\beta = 0.358$, $p < 0.001$), and AISE significantly and positively predicted AIT ($\beta = 0.575$, $p < 0.001$). However, the predictive effect of AIT on IB was not significant ($\beta = 0.010$, $p = 0.844$). Further bootstrap results indicated that the simple indirect effect of AIL on IB through AISE was significant (Effect = 0.116, 95% CI [0.057, 0.181]), whereas the simple indirect effect of AIL on IB through AIT was not significant (Effect = -0.0003 , 95% CI [-0.008 , 0.006]). More importantly, the indirect effect of the alternative serial pathway “AIL $\rightarrow$ AISE $\rightarrow$ AIT $\rightarrow$ IB” was not significant (Effect = 0.002, 95% CI [-0.019 ,

0.030]). This indicates that, after reversing the order of the two mediators, the alternative serial mediation pathway was not supported. By contrast, the serial mediation pathway “AIL → AIT → AISE → IB” in the theoretical model of this study was significant. Therefore, this supplementary analysis provides further support for the theoretically proposed ordering of AIT and AISE.

4.4. Test for Moderated Chain Mediating Effects

To further examine the moderating role of AIA in the model, this study used Hayes’s PROCESS macro (Model 92) to test the moderating effects of AIA on the relevant paths [50]. The regression results showed that the moderating effects of AIA differed across paths in the model (see Table 3). First, in the model with AIT as the outcome variable, the interaction term between AIL and AIA did not reach statistical significance ($\beta = 0.063$, $p = 0.063$, 95% CI $[-0.003, 0.129]$), indicating that the moderating effect of AIA on the association between AIL and AIT was not supported. In the model with AISE as the outcome variable, the interaction term between AIL and AIA was also non-significant ($\beta = -0.013$, $p = 0.670$), suggesting that the moderating effect of AIA on the association between AIL and AISE was not supported either.

Table 3. Testing the moderated chain mediation model using regression analysis.

Outcome Variable	Predictor Variable	Coeff	SE	t	95% CI	F	R ²
					LLCI-ULCI		
AIT	Gender	−0.080	0.106	−0.755	−0.289–0.129	16.488 ***	0.151
	Age	0.029	0.021	1.389	−0.012–0.070		
	AIL	0.134	0.043	3.102 **	0.049–0.218		
	AIA	0.309	0.046	6.788 ***	0.220–0.398		
	AIL × AIA	0.063	0.034	1.865	−0.003–0.129		
AISE	Gender	−0.269	0.087	−3.099 **	−0.439–0.098	51.516 ***	0.438
	Age	0.013	0.017	0.742	−0.021–0.046		
	AIL	0.243	0.036	6.766 ***	0.172–0.314		
	AIT	0.438	0.038	11.559 ***	0.363–0.512		
	AIA	0.146	0.039	3.740 ***	0.070–0.223		
	AIL × AIA	−0.013	0.030	−0.427	−0.071–0.045		
IB	AIT × AIA	0.095	0.027	3.496 ***	0.041–0.148	19.426 ***	0.275
	Gender	0.013	0.100	0.134	−0.183–0.210		
	Age	0.002	0.019	0.108	−0.036–0.040		
	AIL	0.276	0.043	6.423 ***	0.192–0.361		
	AIT	−0.036	0.05	−0.731	−0.134–0.061		
	AISE	0.318	0.054	5.876 ***	0.212–0.424		
	AIA	0.033	0.048	0.696	−0.060–0.127		
	AIL × AIA	0.072	0.035	2.029 *	0.002–0.141		
	AIT × AIA	−0.063	0.041	−1.557	−0.143–0.017		
	AISE × AIA	0.082	0.042	1.969 *	0.0002–0.163		

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

By contrast, the moderating effects of AIA were more evident in the middle and later paths of the model. Specifically, the interaction term between AIT and AIA was significantly associated with AISE ($\beta = 0.095$, $p < 0.001$), indicating that AIA moderated the relationship between AIT and AISE. In addition, both the interaction term between AISE and AIA ($\beta = 0.082$, $p < 0.05$) and the interaction term between AIL and AIA ($\beta = 0.072$, $p < 0.05$) were significantly associated with IB. These results indicate that AIA moderated the associations between AISE and IB, and between AIL and IB, respectively.

To further clarify the specific patterns of the moderating effects of AIA, simple slope analyses were conducted. The results showed that (Figures 2–4), at a high level of AIA (+1 SD), the conditional association between AIT and AISE was stronger (Effect = 0.523, $p < 0.001$), as was the conditional association between AISE and IB (Effect = 0.391, $p < 0.001$). The direct path between AIL and IB also showed a stronger association (Effect = 0.340, $p < 0.001$). At a low level of AIA (−1 SD), these three paths remained significant, but the corresponding effect values were 0.346, 0.239, and 0.207, respectively. Overall, AIA did not significantly moderate the initial paths of the model. Instead, its moderating role was mainly reflected in the strengths of the associations between AIT and AISE, between AISE and IB, and between AIL and IB.

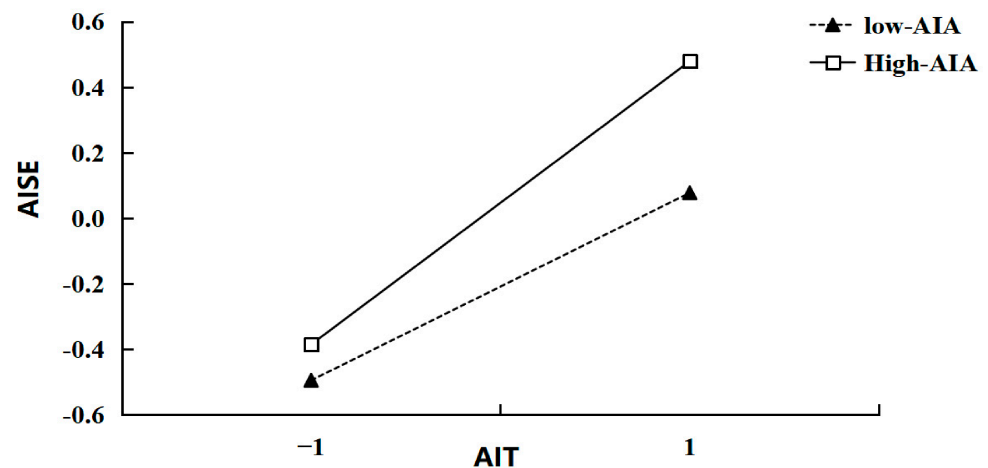


Figure 2. The moderating role of AIA between AIT and AISE.

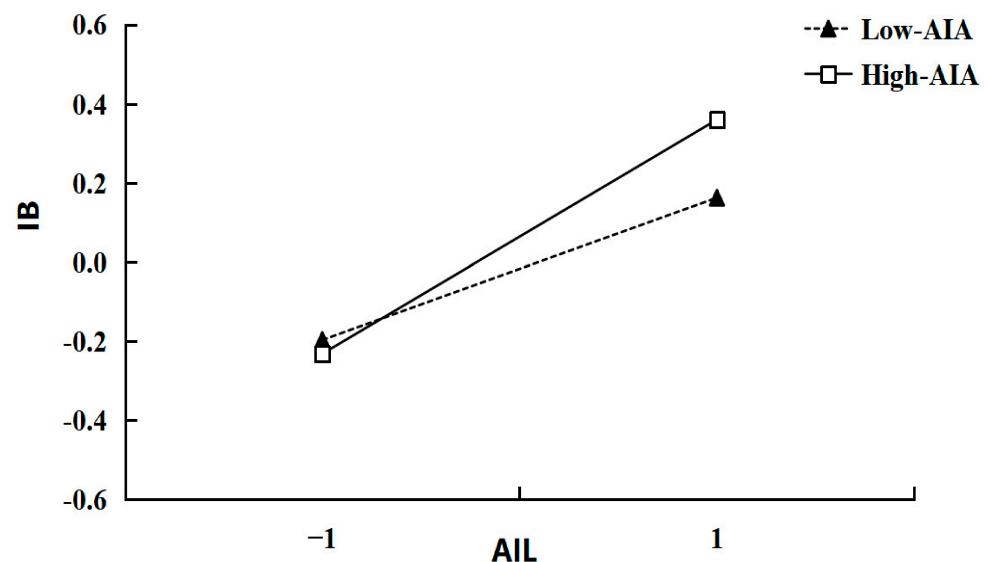


Figure 3. The moderating role of AIA between AIL and IB.

The conditional indirect effect analysis further showed that the indirect effects differed across levels of AIA. For the simple indirect path from AIL to IB through AIT, the confidence intervals included zero under low, mean, and high levels of AIA, indicating that this indirect path was not significant at any level of AIA. By contrast, the serial indirect path from AIL to IB through AIT and AISE showed conditional differences. When AIA was low (−1 SD), the serial indirect effect was not significant (Effect = 0.006, 95% CI [−0.005, 0.020]). When AIA was at the mean level and at a high level (+1 SD), the serial indirect effect

was significant, with effect sizes of 0.017 (95% CI [0.003, 0.033]) and 0.039 (95% CI [0.013, 0.069]), respectively.

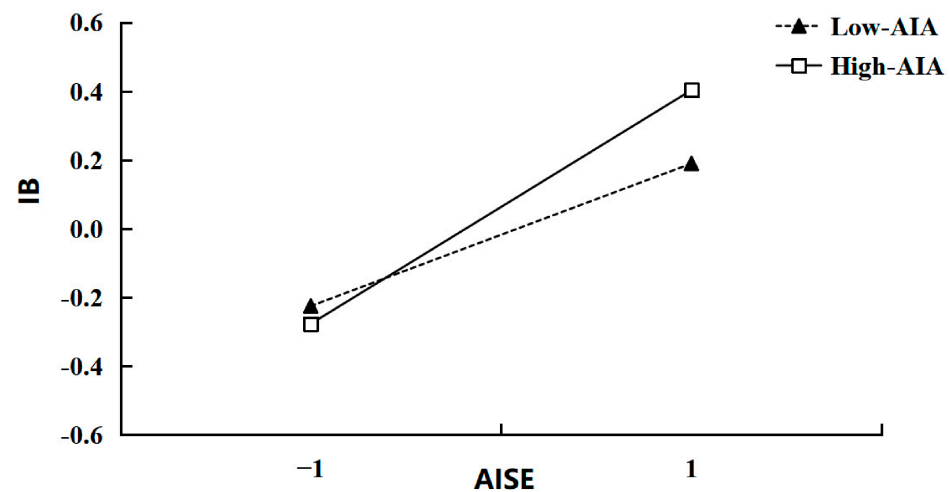


Figure 4. The moderating role of AIA between AISE and IB.

Further comparison of the serial indirect effects under high and low levels of AIA showed that the difference was significant ($\Delta\beta = 0.033$, 95% CI [0.006, 0.063]). This result indicates that AIA moderated the serial indirect pathway linking AIL to IB, thereby supporting the moderated serial mediation effect. Taken together, the findings suggest that AIA did not significantly moderate all paths in the model. Instead, its moderating role was mainly reflected in the latter-stage paths, including AIT $\rightarrow$ AISE, AISE $\rightarrow$ IB, and AIL $\rightarrow$ IB. In other words, at higher levels of AIA, the indirect association between AIL and IB through AIT and AISE was more pronounced.

5. Discussion

5.1. The Relationship Between AIL and University Students' IB

This study found a significant positive relationship between AIL and university students' IB, supporting H1. This finding is consistent with previous research on the role of generative AI in supporting learning performance and innovation-related development. Noy and Zhang's experimental study found that the use of generative AI was associated with improved efficiency and quality in writing tasks [51], while Li also suggested that the immediate and personalised feedback provided by Generative artificial intelligence software may be related to students' deep engagement and the development of innovative thinking [52]. These studies indicate that generative AI can provide external support for students' information processing, knowledge construction, and idea expansion. Building on this evidence, the present study further suggests that whether the external support provided by AI tools is associated with IB also depends on whether students themselves have the capacity to understand, evaluate, apply, and use AI in a responsible manner. IB emphasises individuals' active attempts to generate and implement new ideas, methods, and solutions in authentic learning and practice contexts [53]. Previous research on project-based learning has also shown that integrating digital technologies into authentic task contexts can support the development of students' critical thinking, teamwork, and professional competence [54]. Therefore, the positive relationship between AIL and IB may reflect differences in university students' capacity to embed AI resources into authentic problem-solving and innovative practice.

This result can be interpreted from the perspective of the componential theory of creativity. The theory emphasises that individual innovative performance depends on

the joint support of domain-relevant skills, creativity-relevant processes, and task motivation [55]. In the context of this study, AIL is not merely students' familiarity with how to operate AI tools. More importantly, it reflects whether they can judge, filter, revise, and reorganise AI-generated content, and transform it into a supportive resource for problem clarification, solution comparison, idea refinement, and task advancement. In this way, the information and suggestions provided by AI are more likely to enter students' innovative practice processes and become associated with the generation of new ideas, the trial of new methods, and the implementation of new solutions.

At the same time, the findings of this study should be understood in relation to specific educational and cultural contexts. AI education policies, technological accessibility, academic norms, and students' value judgements regarding AI tools may differ across countries and regions. Based on a sample of university students in Hong Kong, Chan and Hu found that students generally recognised the value of generative AI in personalised learning, writing assistance, and research support [56], while also expressing concerns about accuracy, privacy, and ethical risks. Strzelecki, using a sample of university students in Poland, found that habit, performance expectancy, and hedonic motivation were important factors influencing students' acceptance of ChatGPT [57]. These findings suggest that although the positive relationship between AIL and IB has practical significance, its specific manifestation may still be shaped by educational systems, the climate of technology use, and students' prior experience with AI. Future research should therefore further examine this relationship across different cultural and educational contexts.

5.2. The Mediating Role of AIT

This study found a significant positive relationship between AIL and AIT, whereas the direct path from AIT to IB was not significant. The independent indirect effect of "AIL $\rightarrow$ AIT $\rightarrow$ IB" also failed to reach significance; therefore, H2 was not supported. This result indicates that university students with higher levels of AIL are more likely to develop higher levels of AIT, but such trust does not directly correspond to higher levels of IB. This finding is not entirely consistent with some studies on AI technology acceptance. Previous research has suggested that AIT is an important psychological factor in understanding individuals' acceptance and use of AI technologies, and that it can shape willingness to use AI and attitudes towards its acceptance [58]. However, the present findings further suggest that, in the context of university students' IB, AIT alone may be insufficient to constitute a psychological pathway linking AIL to IB. One possible explanation is that AIT mainly reflects individuals' positive judgements regarding the reliability, functionality, and usability of AI systems, and is primarily related to whether they are willing to approach, accept, or use AI technologies. By contrast, IB is not merely a general form of technology use, but a complex behavioural process involving idea generation, idea promotion, and practical implementation [59]. Therefore, trusting AI does not necessarily mean that individuals can further transform AI-generated content into implementable innovative solutions. For university students, AIT may help reduce uncertainty when they engage with AI tools and foster a certain state of readiness for use. Previous research has noted that AIT is closely related to perceived uncertainty, system explainability, and trust calibration in human–AI interaction [60]. However, for AIT to be further associated with IB, trust alone may not be sufficient; more practice-oriented psychological resources, such as capability beliefs, perceived task control, and sustained behavioural engagement, may also be required. From this perspective, the non-significant independent indirect effect of AIT does not mean that AIT is unimportant. Rather, it suggests that AIT may function more as a preliminary psychological condition linking AI use to innovative practice.

5.3. The Mediating Role of AISE

This study found that AISE significantly mediated the relationship between AIL and university students' IB. Specifically, university students with higher levels of AIL tended to report higher levels of AISE, and those with higher levels of AISE tended to demonstrate higher levels of IB; therefore, H3 was supported. This result is generally consistent with previous research on the relationship between capability beliefs and creative performance. Gong et al. noted that creative self-efficacy plays an important mediating role in the development of individual creativity, suggesting that capability beliefs constitute an important psychological mechanism underlying creative behaviour [61]. The present study extends this perspective to the AI context and further suggests that AISE may be an important psychological pathway linking AIL to IB. More broadly, prior research with adolescent samples has also shown that self-efficacy can serve as an important psychological mechanism through which individual positive beliefs are translated into adaptive developmental outcomes [62]. This provides indirect support for the present finding that AISE functions as a key psychological pathway linking AIL to IB. Self-efficacy theory holds that individuals' judgements about their own abilities shape their behavioural choices, level of engagement, and persistence in complex tasks [63]. In the context of AI use, AISE more specifically reflects individuals' overall belief that they can use AI effectively to complete tasks [64]. Unlike AIT, which mainly reflects judgements about technological reliability, AISE emphasises individuals' agency and sense of control during task performance. Given that IB is characterised by uncertainty and repeated trial and error, AI-related knowledge or trust in AI tools alone may not be sufficient to translate into innovative practice. By contrast, when individuals develop higher levels of AISE, they may be more likely to actively mobilise AI resources in learning and practical tasks, and to maintain stronger behavioural engagement during problem-solving, solution adjustment, and continuous optimisation. From this perspective, AISE represents an important psychological mechanism through which individuals may transform AI-related cognition and skills into actual IB.

5.4. The Chain Mediating Role of AIT and AISE

This study further found that the serial indirect effect of AIT and AISE in the relationship between AIL and IB was significant, supporting H4. This result suggests that the association between AIL and IB may not simply mean that "understanding AI leads to innovative action". Rather, it may involve a process in which students first recognise the value of external technological resources and then form judgements about their own ability to mobilise these resources. This finding is consistent with previous research on the relationships among trust, self-efficacy, and creative outcomes, which suggests that trust may not necessarily correspond directly to creative performance, but may be further related to creative outcomes through capability beliefs such as self-efficacy [65]. From the perspective of conservation of resources theory, when individuals face complex tasks, they tend to identify, acquire, and mobilise valuable resources in order to respond to task demands and achieve their goals [15]. In the context of this study, students with higher levels of AIL may be more likely to recognise the potential value of AI as a resource for learning and problem-solving, and to develop higher levels of AIT on this basis. However, external resources are more likely to enter concrete task practice only when individuals believe that they can effectively mobilise and use them. Expectancy–value theory also suggests that individuals' task engagement is closely related to their judgements about task value and their expectations of success [66]. From this perspective, AIT mainly reflects students' positive judgements about the value, reliability, and usability of AI tools, whereas AISE further reflects their expectations regarding their own ability to use AI resources effectively to complete tasks. The serial association between AIT and AISE suggests that

students with higher levels of AIL may be more likely to identify AI as a valuable resource for learning and problem-solving and, based on trust in this resource, further develop capability beliefs about using AI to advance tasks, which may in turn be associated with their tendency towards innovative action.

5.5. The Moderating Role of AIA

This study found that AIA played a partial moderating role in the relationship between AIL and university students' IB. Specifically, AIA significantly moderated the relationships between AIL and IB, between AIT and AISE, and between AISE and IB; these associations were stronger at higher levels of AIA. In addition, the conditional indirect effect results showed that the serial indirect effect of "AIL $\rightarrow$ AIT $\rightarrow$ AISE $\rightarrow$ IB" was significant only at medium and high levels of AIA, but not at low levels of AIA. Thus, H5c, H5e, and H5f were supported, whereas H5a, H5b, and H5d were not supported. This indicates that AIA did not moderate all paths in the model, but was mainly reflected in the middle and later stages of the model.

The significant moderating paths can be understood through the compensatory effort mechanism in attentional control theory. This theory suggests that although anxiety may consume individuals' cognitive resources and reduce processing efficiency, individuals may also invest greater effort and adopt more active regulatory strategies to maintain task performance [67]. Accordingly, at higher levels of AIA, students may become more sensitive to technological change, capability gaps, and future adaptation pressure. When they already possess a certain level of AIT or AISE, this anxiety experience may be associated with stronger task attention, resource mobilisation, and a greater tendency towards innovative action. Related research has also shown that, under certain conditions, AIA may be positively associated with individuals' AI learning motivation and technology adaptation behaviour [68]. Therefore, in the present study, AIA is better understood as an emotional boundary condition rather than as a purely negative or facilitating factor.

The non-significant moderating paths also have explanatory value. First, AIA did not significantly moderate the relationships between AIL and AIT or between AIL and AISE. This may suggest that the initial stages of the model depend more on students' existing AI knowledge base, technological understanding, and usage experience than on their level of anxiety. Previous research has indicated that students' trust in and use-related judgements about AI are often related to their understanding of AI system capability, transparency, and educational value [69]. Second, AIA did not significantly moderate the relationship between AIT and IB. One possible reason is that IB is not a general form of technology acceptance or use, but requires the joint involvement of capability beliefs, creative engagement, and contextual support. Related research has also shown that IB is usually shaped by both individual psychological resources and external support conditions [70]. Therefore, although AIT may reduce students' uncertainty when engaging with AI tools, it may not directly correspond to IB. Instead, the association between AIT and IB may still need to be manifested through more implementation-oriented psychological resources, such as AISE.

5.6. Practical Implications

First, from the perspective of AIL education, this study found a significant positive relationship between AIL and university students' IB. This suggests that universities should not reduce AIL education to training in tool operation. Instead, they should integrate understanding of AI principles, tool application, output evaluation, ethical judgement, and innovative practice into a coherent training system. Unlike traditional digital literacy education, which mainly emphasises information acquisition, media use, and technical operation, AIL education should further attend to students' ability to evaluate AI-generated

outputs, collaborate with AI, develop ethical responsibility, and apply AI creatively. Previous research has also indicated that the effective advancement of AIL education involves not only the development of students' competencies, but also the coordinated construction of teacher professional development and curriculum support systems [71]. In other words, universities should not only train students to "use AI" but also help them apply AI resources appropriately to authentic problem-solving, research training, and innovative practice on the basis of understanding technological boundaries and potential risks.

Second, from the perspective of AI-assisted innovation teaching, given the important roles of AISE and the serial pathway of AIT → AISE in the model, teachers should not only emphasise students' acceptance of and trust in AI tools, but also pay closer attention to their capability beliefs in using AI to complete complex tasks. Therefore, teachers can use project-based learning, problem-based learning, AI-assisted research training, and interdisciplinary creative tasks to guide students in using AI tools during problem definition, information integration, solution generation, result revision, and outcome presentation. Existing research has also emphasised that STEM education oriented towards complex problems should promote students' creativity, problem-solving ability, and interdisciplinary collaboration through more participatory, practical, and student-centred learning designs [72]. Such teaching designs may help students calibrate their trust in AI tools in authentic tasks, strengthen their sense of control in using AI to advance complex tasks, and further enhance their ability to transform AI resources into innovative solutions.

Third, from the perspective of student support services, this study found that AIA did not moderate all paths in the model, but was mainly reflected in the middle and later stages of the model. This suggests that universities should not regard students' AIA simply as a negative emotion that needs to be eliminated. Rather, it should be understood as an important psychological signal in students' adaptation to AI-enabled learning environments. For students with higher levels of AIA, universities can provide AI use guidance, academic ethics education, career development counselling, and psychological support to help them understand both the opportunities and risks of AI development, and to transform moderate anxiety into risk awareness, learning readiness, and adaptive action. At the same time, universities should attend to differences among students in AI use opportunities, technological foundations, and psychological adaptation, so as to avoid allowing AI education to further widen digital competence gaps among students.

5.7. Research Limitations and Future Prospects

First, this study adopted a cross-sectional design, which limits the extent to which strict causal inferences can be made about the relationships among the variables. Although this study analysed the relationships among AIL, AIT, AISE, AIA, and IB based on a theoretically grounded model, cross-sectional data can only reveal patterns of association among variables and cannot establish causal direction. Future research could employ longitudinal designs, experimental methods, or cross-lagged models to further examine the temporal ordering between AIT and AISE, as well as how AIL is associated with university students' IB over time.

Second, this study mainly relied on self-report questionnaires, which may involve common method bias and subjective reporting bias. Although multiple methods were used to control for and test common method bias, data collected from the same source at the same time point may still be influenced by social desirability, subjective interpretation, and shared measurement methods. Future research could combine multiple data sources, such as teacher ratings, peer evaluations, behavioural tasks, AI platform usage records, or indicators of innovative outcomes, to enhance the robustness of the findings.

Third, this study used convenience sampling, and the sample consisted only of university students from China. The sample structure and local cultural context may limit the generalisability of the findings. The educational application of AI has both global relevance and contextual specificity, and students from different countries and regions may differ in their opportunities to use AI, attitudes towards technology, understanding of academic norms, and perceptions of risk. Cross-cultural research has also shown that university communities from different cultural backgrounds may differ in their perceptions of the educational value of generative AI, academic integrity risks, and institutional responses [73]. Therefore, the findings of this study cannot be directly generalised to all cultural contexts. Future research could expand the sample coverage by including university students from different regions, institutions, disciplines, and year levels, and could conduct cross-cultural comparative studies to examine the applicability of the relationships among AIL, AIT, AISE, AIA, and IB across diverse educational systems and cultural contexts.

6. Conclusions

Drawing on the componential theory of creativity and conservation of resources theory, this study examined the relationship between AIL and university students' IB, with a particular focus on the roles of AIT, AISE, and AIA. The findings showed that: (1) AIL was significantly and positively associated with university students' IB, suggesting that, in AI-enabled learning contexts, AIL is not only an important competence for students to adapt to the age of AI, but also a key entry point for understanding university students' IB in the context of sustainable development in higher education; (2) the independent mediating effect of AIT was not significant, whereas the mediating effect of AISE and the serial mediating pathway of AIT–AISE were significant. This indicates that university students' positive evaluation of AI tools does not necessarily correspond directly to IB; rather, what appears more critical is whether they further develop capability beliefs about using AI resources effectively to complete complex tasks; and (3) AIA showed a partial moderating effect, mainly in the middle and later stages of the model. This suggests that AIA should not be simply regarded as a purely negative psychological experience, but should instead be understood as an emotional boundary condition in students' adaptation to AI-enabled learning environments.

Overall, from an integrated perspective of AIL, AIT, AISE, and AIA, this study further demonstrates that university students' IB is not merely related to the use of AI tools, but is also jointly associated with students' understanding and evaluation of AI resources, their capability beliefs, and their emotional adaptation to AI. Theoretically, these findings help extend understanding of the psychological mechanisms associated with university students' IB in AI-enabled learning contexts. Practically, they provide implications for universities seeking to optimise AIL education, implement AI-assisted innovation teaching, and improve student support services for AI-enabled learning.

Author Contributions: Conceptualization, Y.Z. and X.L.; Methodology, Y.Z.; Validation, Y.Z. and X.L.; Formal analysis, Y.Z. and M.Z.; Investigation, S.L., M.Z. and B.L.; Resources, S.L.; Data curation, S.L.; Writing—original draft, Y.Z.; Writing—review & editing, S.L. and M.Z.; Supervision, S.L., M.Z. and X.L.; Funding acquisition, M.Z. and X.L. All authors have read and agreed to the published version of the manuscript.

Funding: This research was supported by the 2024 Henan Provincial Higher Education Teaching Reform Research and Practice Project (Grant No. 2024SJGLX0663) and the 2026 Postgraduate Research and Practice Innovation Project of Henan Normal University (Grant No. YB202608).

Institutional Review Board Statement: The study was conducted in accordance with the Declaration of Helsinki, and approved by the Ethics Committee of Zhengzhou Shengda University (2026-0320) on 20 March 2026.

Informed Consent Statement: Informed consent for participation was obtained from all subjects involved in the study.

Data Availability Statement: The data presented in this study are available on request from the corresponding author.

Conflicts of Interest: The authors declare no conflict of interest.

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