

Research Article

AI Education Exposure and Its Effects on Innovation Capability and Career Adaptability Among Chinese Undergraduate Students

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ABSTRACT





Artificial intelligence (AI) is increasingly embedded in higher education, yet empirical evidence remains limited regarding whether students' AI-Supported Learning Experience (ASLE) is associated with broader developmental outcomes such as innovation ability and career adaptability within a single explanatory model. This study employed a quantitative cross-sectional survey design involving 411 undergraduate students from four universities in China who had prior exposure to AI-supported learning environments. Data were analyzed using IBM SPSS and AMOS through descriptive statistics, reliability testing, confirmatory factor analysis (CFA), structural equation modelling (SEM), and bootstrapped mediation analysis with 5,000 resamples. The findings indicate that ASLE positively predicts innovation ability ($\beta = 0.329$, $p < 0.001$) and career adaptability ($\beta = 0.231$, $p < 0.001$). Innovation ability also positively predicts career adaptability ($\beta = 0.284$, $p < 0.001$). In addition, innovation ability significantly partially mediates the relationship between ASLE and career adaptability (indirect effect = 0.093, $p < 0.001$; 95% CI [0.05, 0.15]). The model explained 10.8% of the variance in innovation ability and 17.7% of the variance in career adaptability. The study suggests that AI-supported learning in higher education may contribute to students' future-oriented development not only by familiarizing them with emerging technologies, but also by strengthening innovation-related capability that supports adaptive career readiness. The findings clarify the construct boundary of ASLE and highlight the importance of pedagogically meaningful AI integration in designing learning environments that better prepare students for technology-driven labor markets.

KEYWORDS creative problem solving • digital pedagogy • innovation and infrastructure • structural equation modelling • technology-enhanced learning • quality education

ARTICLE CITATION

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1. INTRODUCTION

Artificial intelligence (AI) is rapidly transforming higher education by reshaping how students access knowledge, complete academic tasks, receive feedback, and participate in digital learning environments. Recent scholarship shows that AI is no longer discussed merely as an emerging educational technology, but as a major force influencing pedagogy, assessment, student engagement, and institutional innovation. For example, Bond et al. [1] and Wang et al. [2] noted that AI-related research in higher education has expanded substantially, covering not only intelligent tutoring systems and adaptive learning platforms but also broader questions concerning educational effectiveness, ethics, and institutional implementation. In a similar vein, Crompton and Burke [3] argued that the field has moved beyond simple questions of adoption toward deeper concerns about how AI changes teaching and learning processes in higher education.

Despite this growing attention, the literature remains uneven in its emphasis. Much of the existing research has concentrated on AI adoption, institutional readiness, governance, policy, academic integrity, and AI literacy [4]-[9]. While these strands are important, they do not sufficiently explain how students' actual engagement with AI-supported learning environments contributes to broader developmental outcomes. In other words, higher education research has made meaningful progress in discussing how universities should regulate, integrate, or teach AI, but less progress in clarifying how AI-supported learning experiences affect the development of competencies that matter for students' longer-term academic and professional futures. This imbalance is also highlighted by Zawacki-Richter et al. [10], who observed that much of the early AI-in-higher-education literature emphasized systems and applications more than student-centered developmental processes.

Among the outcomes that deserve greater attention, innovation ability and career adaptability are particularly important. Innovation ability refers to students' capacity to generate original ideas, solve problems creatively, experiment with alternatives, and apply knowledge in new or unfamiliar contexts. This ability is increasingly viewed as a core attribute of graduates who must function in dynamic, knowledge-intensive, and technology-rich environments. At the same time, career adaptability has become a central psychosocial resource for navigating uncertain and changing career pathways. According to Savickas and Porfeli [11], career adaptability reflects the readiness and resources individuals use to cope with vocational tasks, career transitions, and work-related uncertainty. Career adaptability is closely associated with broader career resources and long-term career success [12]-[14]. In the context of AI-driven labor market transformation, the ability to innovate and the ability to adapt are no longer peripheral graduate attributes; rather,

they are increasingly central to employability and professional resilience.

At the same time, the educational impact of AI should not be viewed as automatically positive. Research suggests that AI-supported learning environments can improve personalization, feedback, interactivity, and learner support when they are meaningfully integrated into pedagogy. For instance, Ouyang and Jiao [15] conceptualized AI in education through multiple paradigms that extend beyond automation and include intelligent support for learning processes. Likewise, Lin and Qiu [16] found that AI-integrated educational applications were positively related to college students' creativity and academic emotions, indicating that AI-supported learning may help create more engaging and generative learning experiences. However, the benefits of AI are not unconditional. If used passively or without pedagogical structure, AI may encourage superficial dependency rather than deeper learning. This is why the present study treats AI not merely as a technological tool, but as part of a broader learning experience whose developmental value depends on how it is embedded in students' academic environment.

For this reason, the present study uses the construct AI-Supported Learning Experience (ASLE) rather than the broader and more ambiguous term "AI education." This distinction is conceptually important. The focal interest of this study is not formal AI curriculum design, AI literacy instruction, or specialized AI training in the narrow sense. Instead, ASLE refers to students perceived exposure to AI-supported tools, AI-based academic activities, and AI-enhanced learning support within their university courses. This construct more accurately reflects the operationalization used in the manuscript and helps avoid conceptual conflation with adjacent constructs such as AI literacy, AI competence, or AI policy education. The need for such conceptual precision has been emphasized by Bond et al. [1], who called for greater rigor and clarity in AI-in-higher-education research, and by Southworth et al. [4], who distinguished AI-across-the-curriculum initiatives from more narrowly defined AI literacy efforts.

The present study is theoretically grounded in Social Cognitive Career Theory (SCCT) and Self-Determination Theory (SDT). From the SCCT perspective, as proposed by Lent et al. [17], learning experiences play a key role in shaping individuals' competence beliefs, agency, and future-oriented behavioral outcomes. This makes SCCT particularly relevant for understanding how AI-supported learning experiences may influence students' innovation-related capabilities and adaptive career resources. From the SDT perspective, Ryan and Deci [18]-[20] argued that developmental growth is more likely when learning environments support autonomy, competence, and meaningful engagement. Applied to the current study, AI-supported learning environments may become developmentally significant when they encourage students to engage actively with challenging academic

tasks, experiment with new solutions, and experience growing competence in technology-rich learning situations.

Innovation ability is positioned as the most plausible mediating mechanism linking ASLE and career adaptability. AI-supported learning environments often expose students to iterative feedback, interactive inquiry, problem-solving, and knowledge application in unfamiliar situations. These experiences may strengthen flexibility, creativity, and experimentation, all of which are central dimensions of innovation ability. AI-integrated learning can foster creativity-related outcomes, while broader work on student innovation and technology-enhanced learning also points in the same direction [9], [16], [21], [22]. In turn, students with stronger innovation ability are likely to be better prepared to interpret uncertainty constructively, respond to emerging opportunities, and adapt more effectively to changing occupational demands. From this perspective, innovation ability is not merely another outcome of AI-supported learning; it is also a mechanism through which AI-supported learning may translate into broader adaptive career readiness.

A major limitation of the current literature is that it treats AI-supported learning, innovation-related outcomes, and career adaptation as adjacent rather than integrated domains. While reviews of AI in higher education consistently show rapid growth in research on implementation, perceptions, governance, and classroom applications, they also indicate limited conceptual integration around student developmental outcomes [23]–[26]. In parallel, research on career adaptability has mainly emphasized psychosocial and contextual predictors such as proactive personality, college experience, academic engagement, and career education participation [27]–[29], with far less attention to AI-supported learning as a formative educational condition. This disconnect is increasingly problematic because higher education institutions are now expected not only to digitalize learning, but also to prepare students for innovation-intensive and uncertainty-laden labor markets. Recent evidence that AI-related competencies are linked to graduate employability further underscores this need [30], [31]. Therefore, a more integrated framework is needed to explain whether AI-Supported Learning Experience enhances both innovation ability and career adaptability, and whether innovation ability serves as the mediating mechanism connecting the two.

The Chinese higher-education context offers a timely setting for examining these relationships. China has become a major hub of AI-in-higher-education research and institutional experimentation, with universities increasingly integrating AI-supported tools, AI-related courses, and digitally enhanced teaching practices into undergraduate education [3], [32], [33]. At the same time, Chinese universities face growing pressure to cultivate students' innovation capacity and employability in response to a rapidly digitalizing economy [34], [35].

National policy also reinforces this direction, as the Ministry of Education of the People's Republic of China [36] has identified AI and educational transformation as strategic priorities. In this context, examining the relationship between AI-Supported Learning Experience (ASLE), innovation ability, and career adaptability is both empirically relevant and practically important.

Accordingly, the present study addresses this gap by examining whether AI-Supported Learning Experience significantly predicts students' innovation ability and career adaptability, and whether innovation ability mediates the relationship between ASLE and career adaptability. This study contributes to the literature in three ways. First, it extends AI-in-higher-education research beyond technology adoption and institutional discourse by focusing on broader developmental student outcomes. Second, it strengthens conceptual clarity by treating ASLE as an experiential construct rather than conflating it with AI literacy or formal AI education. Third, it proposes and tests an integrated mediation model that explains how AI-supported learning may contribute to future-oriented career readiness through the development of innovation ability. In doing so, the study positions AI not simply as an instructional technology, but as a pedagogically mediated developmental condition with implications for both innovation and employability in higher education.

2. LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

2.1. Conceptualizing AI-Supported Learning Experience

Artificial intelligence has become increasingly embedded in higher education through adaptive learning systems, intelligent tutoring, generative tools, automated feedback, and data-informed instructional support. Recent reviews suggest that research in this area has expanded rapidly; however, much of the literature continues to focus on adoption patterns, institutional implementation, governance, ethics, and student perceptions, rather than on integrated student-development outcomes [37]–[39]. In this respect, AI in higher education is better understood not merely as a technological intervention, but as a pedagogically mediated learning condition whose effects depend on how AI tools are embedded in teaching and learning processes.

Within this broader context, the present study adopts the construct AI-Supported Learning Experience (ASLE) rather than the broader and more ambiguous term "AI education." This distinction is important because the study does not focus on formal AI curriculum design or AI literacy instruction in a narrow sense, but on students perceived exposure to AI-supported tools, AI-based learning activities, and AI-enhanced academic engagement in university settings. Prior scholarship has emphasized that AI in education is shifting from

technology-centered delivery toward more learner-centered and collaborative paradigms, making conceptual precision essential when examining student experience [15], [23], [40]. Moreover, recent evidence indicates that the educational benefits of AI are conditional rather than uniformly positive, as AI tools appear most effective when integrated with interactive pedagogies such as project-based learning, scaffolded feedback, and active inquiry [41], [42].

2.2. AI-Supported Learning Experience and Innovation Ability

Innovation ability refers to students' capacity to generate novel ideas, experiment with alternative approaches, solve problems creatively, and transfer knowledge to unfamiliar situations. In higher education, this capability is increasingly recognized as a strategic graduate attribute because contemporary learning and work environments require flexibility, creative problem-solving, and the ability to respond constructively to novelty and complexity. Technology-enhanced learning environments may support this process when they encourage exploration, collaboration, iterative revision, and applied inquiry. For example, Li et al. [43] showed that technology-enhanced higher education curricula can foster creativity and entrepreneurship development when learning design supports students' autonomy, competence, and active participation.

ASLE is theoretically relevant to innovation ability because AI-supported learning environments often expose students to rapid feedback, interactive problem-solving, iterative refinement, and knowledge application in non-routine contexts. AI-supported learning can move beyond automation toward learner collaboration and empowerment, thereby creating opportunities for deeper engagement and higher-order thinking [15]. Similarly, Lin and Qiu [16] found that AI-integrated educational applications were positively associated with college students' creativity and academic emotions, while Long et al. [42] emphasized that AI's educational value is amplified when pedagogical strategies promote active participation and inquiry rather than passive tool use. Taken together, these studies suggest that ASLE may function as a favorable learning condition for the development of innovation ability, although direct empirical evidence remains limited and fragmented.

2.3. AI-Supported Learning Experience and Career Adaptability

Career adaptability refers to the psychosocial resources individuals use to prepare for, manage, and respond to career-related tasks, transitions, and uncertainties. Savickas and Porfeli [11] conceptualized career adaptability as a multidimensional construct that enables individuals to navigate changing career environments, while Haenggli and Hirschi [12] showed that it is closely associated with broader career resources and career

success. In higher education, career adaptability is increasingly important because students must prepare not only for workforce entry, but also for continuous reskilling and occupational change in digitally transformed labor markets.

ASLE may contribute to career adaptability because AI-supported learning can familiarize students with emerging technologies, dynamic work practices, and problem-solving demands associated with contemporary employment contexts. Southworth et al. [4] argued that AI-related curricular innovation in higher education should enhance students' future readiness, and Portocarrero Ramos et al. [30] found that AI skills are positively associated with graduate employability. Long et al. [42] highlighted that AI in higher education is most effective when embedded in pedagogically meaningful contexts, suggesting that AI-supported learning may also strengthen students' confidence in dealing with future-oriented challenges. Although prior studies have more often examined AI literacy, employability, or engagement than career adaptability directly, the existing evidence provides a reasonable basis for positioning ASLE as a potential predictor of career adaptability.

2.4. Innovation Ability and Career Adaptability

Innovation ability may itself serve as an important antecedent of career adaptability. Students who are able to generate ideas, test alternatives, and respond creatively to unfamiliar situations are likely to be better equipped to manage uncertainty and transition in academic and professional settings. Although prior studies on career adaptability have not always used the term "innovation ability," they consistently indicate that adaptability is shaped by higher-order personal resources associated with agency, flexibility, engagement, and developmental experience. Fang et al. [28] demonstrated that proactive personality and college experience are associated with stronger career adaptability, while Oliveira and Marques [27] found that career adaptability is meaningfully related to academic engagement.

Innovation ability can be interpreted as one such higher-order resource. Students with stronger innovation ability are more likely to approach problems proactively, generate options under uncertainty, and reinterpret changing conditions as opportunities rather than threats. In an economy increasingly shaped by AI, automation, and shifting skill requirements, such capabilities are likely to support adaptive career readiness. Moreover, Pang et al. [29] showed that career adaptability functions as an important mechanism in students' academic self-efficacy development, further underscoring its developmental significance. Even so, direct empirical studies linking innovation ability and career adaptability remain limited, making this relationship important to test in the present model.

To clarify the position of the present study within the existing literature, Table 1 summarizes representative

prior studies on artificial intelligence in higher education, innovation-related outcomes, and career adaptability,

while also highlighting the specific research gap addressed in this study.

Table 1. Summary of Prior Studies and Identified Research Gaps

Author(s), Year	Context / Sample	Core Variables / Focus	Main Findings	Specific Limitation / Gap
Bond et al. (2024) [1]	Higher education AI literature	Ethics, collaboration, rigor, and conceptual trends	AI-in-higher-education research is expanding rapidly, but stronger conceptual clarity, ethics, and methodological rigor are still needed.	Review-based; does not test direct student-level developmental relationships among specific outcomes.
Crompton and Burke (2023) [3]	138 studies in higher education (2016–2022)	Publication trends, research foci, contexts, methods	Research on AI in higher education has grown sharply, with strong attention to implementation, applications, and instructional use.	Focus remains broad and field-mapping in nature; limited integration of innovation and career-related outcomes in one model.
Ouyang, Zheng, and Jiao (2022) [23]	Online higher education empirical studies	AI-supported teaching, learning processes, and educational functions	AI can support learning performance, personalized instruction, and feedback in higher education contexts.	Focused largely on online higher education and educational functions, it does not address innovation ability and career adaptability jointly.
Lin and Chen (2024) [16]	College students and teachers	Creativity, academic emotions, and attitudes toward AI-integrated learning	AI-integrated educational applications can stimulate creativity and engagement, but their effects are nuanced and depend on implementation.	Focused primarily on creativity and academic emotions, it does not address career adaptability or mediation mechanisms.
Portocarrero Ramos et al. (2025) [30]	University graduates	AI competencies and employability	AI-related competencies are associated with graduates' employability and readiness for labor-market participation.	Focuses on AI skills rather than AI-supported learning experience; does not include innovation ability as a mechanism.
Fang et al. (2024) [28]	Higher vocational college students	Proactive personality, college experience, career adaptability	Career adaptability is shaped by personal and contextual resources, with college experience acting as a mediator.	Not AI-focused; does not consider technology-enhanced learning as an antecedent of career adaptability.
Oliveira and Marques (2024) [27]	Higher education students	Career adaptability, academic engagement, life satisfaction	Career adaptability and academic engagement significantly contribute to students' life satisfaction.	Does not examine AI-supported learning or innovation ability in the same framework.
Pang et al. (2025) [29]	Students in an educational transition context	Career education participation, career adaptability, learning engagement, and academic self-efficacy	Career adaptability operates as an important mediating mechanism in students' developmental outcomes.	Focuses on career education rather than AI-supported learning; no innovation-related mechanism is tested.
This study (2026)	411 undergraduates from four universities in China	AI-Supported Learning Experience, innovation ability, and career adaptability	ASLE is positively associated with innovation ability and career adaptability, and innovation ability partially mediates the relationship between ASLE and career adaptability.	Cross-sectional and self-reported design; generalizability may be limited to similar higher-education contexts.

2.5. Conceptual Framework

This study proposes a mediation framework in which AI-Supported Learning Experience (ASLE) acts as the exogenous variable, innovation ability as the mediator, and career adaptability as the endogenous variable. In line with recent higher-education AI research, AI-supported learning is most developmentally meaningful

when it is embedded in feedback-rich, interactive, and problem-based learning environments rather than treated as mere technological exposure [44], [45].

Within this framework, a stronger ASLE is expected to enhance innovation ability because AI-supported learning often encourages experimentation, inquiry, and creative problem-solving. This logic is supported by evidence showing that AI-integrated learning can foster creativity

and that its educational effects depend strongly on active pedagogy [16], [42].

In turn, innovation ability is expected to strengthen career adaptability, as students who are more flexible, creative, and solution-oriented are better prepared to cope with career uncertainty and changing labor-market demands. This assumption is consistent with career adaptability theory and Social Cognitive Career Theory, which emphasize that learning experiences shape adaptive career resources [11], [12], [46], [47].

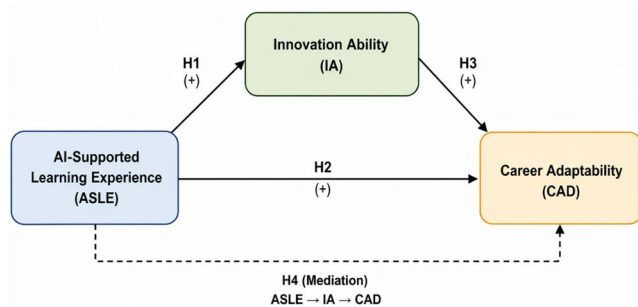


Figure 1. Conceptual framework of the study showing the direct effects of AI-Supported Learning Experience (ASLE) on innovation ability (IA) and career adaptability (CAD).

2.6. Hypothesis Development

2.3.1. Direct effect of AI-supported learning experience on innovation ability

AI-Supported Learning Experience (ASLE) is expected to enhance students' innovation ability because AI-supported learning environments can expand opportunities for experimentation, immediate feedback, exploratory inquiry, and iterative knowledge application. When AI is embedded in pedagogically meaningful learning activities, students are not merely exposed to digital tools. However, they are encouraged to test alternatives, refine ideas, and solve problems in more adaptive and creative ways. In this sense, ASLE may function as a developmental learning condition that supports higher-order thinking and novel idea generation. Prior studies have shown that AI-supported and technology-enhanced learning environments can foster creativity, deeper engagement, and more active forms of inquiry, particularly when learning designs encourage participation rather than passive tool use [15], [16], [42]. Therefore, students who report stronger ASLE are likely to demonstrate stronger innovation ability.

H1: AI-Supported Learning Experience (ASLE) positively influences students' innovation ability (IA).

2.6.2. Direct effect of AI-supported learning experience on career adaptability

ASLE is also expected to positively influence career adaptability because learning in AI-supported environments may help students become more familiar with technological change, dynamic problem-solving

demands, and emerging digital work practices. Such learning experiences may strengthen students' confidence in dealing with uncertain and evolving career tasks by exposing them to future-oriented learning conditions that resemble contemporary professional environments. From this perspective, ASLE may contribute not only to academic development but also to students' psychosocial readiness to manage career transitions and occupational uncertainty. Although prior research has more often linked AI-related learning to engagement, employability, and AI-related competence than directly to career adaptability, the available evidence suggests that AI-supported learning can strengthen students' future readiness and preparedness for technology-driven labor markets [48]–[50]. Accordingly, students with richer ASLE are expected to show higher career adaptability.

H2: AI-Supported Learning Experience (ASLE) positively influences students' career adaptability (CAD).

2.6.3. Direct effect of innovation ability on career adaptability

Innovation ability is further expected to positively influence career adaptability because students who are capable of generating alternatives, experimenting with solutions, and responding creatively to unfamiliar situations are generally better equipped to cope with uncertainty and change. Career adaptability reflects an individual's capacity to prepare for and manage career-related transitions, and such capacity is likely to depend on flexible, agentic, and solution-oriented personal resources. In this regard, innovation ability is conceptually important because it reflects not only creativity, but also proactive cognitive flexibility and constructive problem-solving under novel conditions. Prior research on career adaptability has emphasized the importance of personal resources such as proactive personality, academic engagement, and developmental support, which collectively suggest that adaptability is strengthened by capacities that enable individuals to respond effectively to change [27]–[29]. Therefore, students with stronger innovation ability are expected to exhibit stronger career adaptability.

H3: Innovation ability (IA) positively influences students' career adaptability (CAD).

2.6.4. Mediating effect of innovation ability (IA) in the relationship between AI-supported learning experience (ASLE) and career adaptability (CAD).

AI-Supported Learning Experience (ASLE) may influence students' career adaptability not only directly but also indirectly through innovation ability. AI-supported learning environments expose students to exploratory inquiry, iterative idea refinement, and problem-solving in dynamic and unfamiliar contexts, which can strengthen

their capacity to generate alternatives, think flexibly, and respond creatively to change. These innovative capacities are, in turn, highly relevant to career adaptability because they enable students to cope more effectively with career-related uncertainty, transitions, and evolving work demands. Prior studies suggest that AI-supported learning can foster higher-order thinking, creativity, and active inquiry [15], [16], while career adaptability is strengthened by agentic and flexible personal resources [27], [51]. Accordingly, innovation ability is expected to serve as an explanatory mechanism through which ASLE enhances students' career adaptability.

H4: Innovation ability (IA) mediates the relationship between AI-Supported Learning Experience (ASLE) and students' career adaptability (CAD).

3. MATERIALS AND METHODS

3.1. Research Design

This study employed a quantitative, cross-sectional survey design to examine the relationships among AI-Supported Learning Experience (ASLE), innovation ability, and career adaptability among undergraduate students in four universities in China that had incorporated AI-related courses, AI-supported learning activities, or AI-enabled instructional tools into undergraduate teaching. A cross-sectional design was appropriate because the study aimed to test theoretically specified associations among latent constructs and to evaluate a mediation model using structural equation modelling (SEM), rather than to establish strong causal inference. To improve methodological transparency and reporting quality, the study design and reporting structure were aligned with established guidance for cross-sectional and internet-based survey research.

3.2. Participants, Sampling and Data Collection

Purposive sampling was used because the study required respondents with prior exposure to AI-supported learning environments. Eligible participants were undergraduate students who had completed at least one AI-related course or had direct experience using AI-supported tools, adaptive learning systems, or AI-based academic activities within their coursework. Students without such exposure were excluded. This sampling strategy was appropriate because the focal construct, ASLE, refers to students perceived experience of AI-supported learning rather than general attitudes toward AI.

Data were collected from September to December 2024, using an online questionnaire distributed through departmental mailing lists, course communication groups, and instructor-assisted circulation in eligible programs. A total of 470 students were invited to participate, 423 questionnaires were returned, and 411 valid responses

were retained after data screening, yielding a valid response rate of 87.4%.

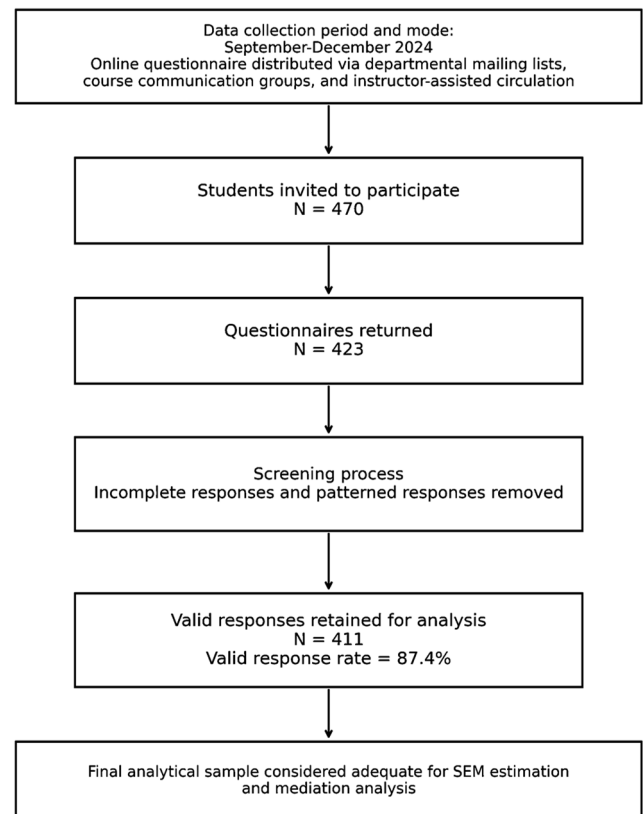


Figure 2. Flow diagram of participant recruitment, response screening, and final analytic sample selection.

Given the modest complexity of the hypothesized SEM model, the final sample was considered adequate for stable model estimation and mediation testing. Contemporary SEM guidance also recommends justifying sample adequacy in relation to model complexity and statistical power, rather than relying solely on rigid rules of thumb.

3.3. Instrument Development and Measures

Data were collected using a structured questionnaire adapted from prior studies on AI-supported learning in higher education, innovation-related capability, and career adaptability. In line with the conceptual focus of the study, the focal predictor was labelled "AI-Supported Learning Experience (ASLE)" rather than "AI education," because the items capture students' perceived exposure to AI-supported tools, activities, and learning benefits, rather than formal curriculum design or AI literacy as a competency domain.

The measurement model comprised three reflective latent constructs: AI-Supported Learning Experience, Innovation Ability, and Career Adaptability. Each construct was operationalized using four items, and all items were measured on a five-point Likert scale ranging from 1 = strongly disagree to 5 = strongly agree. Minor

wording refinements were introduced to improve contextual fit for higher education and the Chinese-language administration. The full item wording and source basis are presented in Table 2. Reflective

specification was retained because the indicators were treated as manifestations of the underlying constructs rather than as formative components [52], [53].

Table 2. Research Instruments

Construct	Item	Questionnaire	Sources
AI-Supported Learning Experience (ASLE)	ASLE1	My courses exposed me to AI-supported learning tools.	Adapted and synthesized from Balabdaoui et al. [54]; Lin & Chen [16]
	ASLE2	AI-based learning activities helped me engage with complex academic tasks.	Adapted and synthesized from Balabdaoui et al. [54]; Heil et al. [55]
	ASLE3	I gained meaningful learning experience through AI-related educational technologies.	Adapted and synthesized from Balabdaoui et al. [54]; Heil et al. [55]
	ASLE4	AI technologies enhanced my learning experience during university courses.	Adapted and synthesized from Balabdaoui et al. [54]; Lin & Chen [16]
Innovation Ability (IA)	IA1	I can generate creative solutions to difficult problems.	Adapted and synthesized from Selznick & Mayhew [56]; Keinänen et al. [57]
	IA2	I am willing to experiment with new approaches when solving academic tasks.	Adapted and synthesized from Keinänen et al. [57]; Keinänen & Kairisto-Mertanen [58]
	IA3	I can apply what I learn to new and unfamiliar situations.	Adapted and synthesized from Selznick & Mayhew [56]; Keinänen et al. [57]
	IA4	I enjoy exploring innovative solutions to academic challenges.	Adapted and synthesized from Selznick & Mayhew [56]; Keinänen & Kairisto-Mertanen [58]
Career Adaptability (CA)	CA1	I feel prepared to deal with changes in my future career.	Adapted from Maggiori et al. [59]; Yu et al. [60]
	CA2	I am confident in handling new career-related challenges.	Adapted from Maggiori et al. [59]; Yu et al. [60]
	CA3	I actively think about and prepare for my future career.	Adapted from Maggiori et al. [59]; Yu et al. [60]
	CA4	I feel capable of adapting to new career opportunities.	Adapted from Maggiori et al. [59]; Yu et al. [60]

3.3.1. AI-Supported Learning Experience

AI-Supported Learning Experience refers to students perceived exposure to and engagement with AI-supported learning environments, including AI-driven tools, AI-based academic activities, and AI-enhanced learning support embedded in university courses. The construct does not measure formal AI curriculum design or AI literacy in the narrow sense. Instead, it captures how students experienced AI as part of their learning process. The construct was measured using four reflective indicators assessing exposure to AI-supported learning tools, engagement with AI-based academic activities, meaningful learning through AI-related educational technologies, and the extent to which AI enhanced students' learning experience.

3.3.2. Innovation Ability

Innovation ability refers to students perceived capacity to generate novel ideas, experiment with alternative approaches, and apply knowledge in new or unfamiliar situations. In the present study, this construct was measured using four reflective items capturing creative

problem solving, willingness to experiment, transfer of learning, and interest in innovative solutions to academic challenges.

3.3.3. Career Adaptability

Career adaptability refers to students' readiness and confidence in dealing with career transitions, responding to new professional challenges, and adapting to changing labor-market demands. The construct was measured using four reflective items assessing preparedness for change, confidence in facing career-related challenges, proactive career thinking, and perceived ability to adapt to new opportunities.

3.4. Translation and Pilot Testing

The questionnaire was initially prepared in English and then translated into Chinese using a translation and back-translation procedure to enhance semantic accuracy and conceptual equivalence between the two language versions. This approach is widely recommended in cross-cultural survey research because it helps ensure that translated items preserve the meaning of the original

instrument while remaining understandable in the target language context. After translation refinement, a pilot test involving 30 students was conducted to assess item clarity, wording, and overall questionnaire flow. Feedback from the pilot resulted in minor revisions to wording and formatting, and the pilot responses indicated acceptable preliminary internal consistency across the three constructs.

3.5. Data Analysis

The data were analyzed using IBM SPSS and AMOS. SPSS was used for data screening, descriptive statistics, and initial reliability analysis, whereas AMOS was used for confirmatory factor analysis (CFA) and structural equation modelling (SEM). SEM was selected because it allows the simultaneous estimation of relationships among multiple latent constructs and is especially suitable for testing direct and indirect effects within a theoretically specified model.

The analysis followed a two-step approach. First, the measurement model was evaluated through CFA. Internal consistency was assessed using Cronbach's alpha and composite reliability (CR). Convergent validity was examined through standardized factor loadings, CR, and average variance extracted (AVE), while discriminant validity was assessed using the Fornell–Larcker criterion [61]. In line with established recommendations, evidence of acceptable convergent validity was judged using

multiple criteria rather than a single statistic. Second, after establishing an adequate measurement model, the structural model was estimated to test the hypothesized direct paths from ASLE to innovation ability, from ASLE to career adaptability, and from innovation ability to career adaptability [52], [62].

Model fit was evaluated using multiple global fit indices, including the chi-square to degrees-of-freedom ratio (χ^2/df), comparative fit index (CFI), Tucker–Lewis index (TLI), root mean square error of approximation (RMSEA), and standardized root mean square residual (SRMR) [63]–[66]. Following common SEM guidance, model adequacy was interpreted using a combination of fit indices rather than any single cut-off value [67].

4. RESULTS

4.1. Respondent Profile and Descriptive Statistics

To provide contextual background for the SEM analysis, the respondent profile and descriptive statistics were first examined. The sample was relatively balanced by gender, consisting of 214 males (52.1%) and 197 females (47.9%). Most respondents were aged 21–23 years (48.9%), and the largest proportion was in the third year of study (29.9%). In addition, 56.7% of respondents had taken more than one AI-related course, indicating that the sample was substantively appropriate for examining ASLE.

Table 3. Respondents' demographics (N=411)

Variable	Category	Frequency	Percentage
Gender	Male	214	52.1%
	Female	197	47.9%
Age	18–20 years	146	35.5%
	21–23 years	201	48.9%
	24 years and above	64	15.6%
Year of Study	First year	88	21.4%
	Second year	116	28.2%
	Third year	123	29.9%
	Fourth year and above	84	20.5%
Exposure to AI Courses	One AI-related course	178	43.3%
	More than one AI-related course	233	56.7%

Table 4. Descriptive statistics

Variable	Mean (M)	Standard Deviation (SD)	Range	Skewness	Kurtosis
AI-Supported Learning Experience	3.61	0.56	2.00–5.00	-0.14	0.05
Innovation Ability	3.74	0.62	2.50–5.00	-0.29	-0.13
Career Adaptability	4.35	0.69	3.00–5.00	-0.32	0.11

Descriptive statistics for the main study variables are reported in Table 4. Among the three focal constructs,

career adaptability recorded the highest mean score ($M = 4.35$, $SD = 0.69$), followed by innovation ability ($M = 3.74$,

SD = 0.62) and AI-Supported Learning Experience (M = 3.61, SD = 0.56). The observed skewness and kurtosis values were small, suggesting that the item distributions did not show serious deviations from normality for SEM analysis.

4.2. Measurement Model Assessment

4.2.1. Correlation Analysis

Pearson correlation analysis was conducted as a preliminary examination of the relationships among the study variables. In Table 5, ASLE was positively and significantly correlated with innovation ability ($r = 0.329$, $p < 0.001$) and career adaptability ($r = 0.325$, $p < 0.001$). Innovation ability was also positively and significantly correlated with career adaptability ($r = 0.360$, $p < 0.001$).

Table 5. Pearson Correlation Matrix

Variable	ASLE	IA	CA
AI-Supported Learning Experience	1		
Innovation Ability	0.329**	1	
Career Adaptability	0.325**	0.360**	1

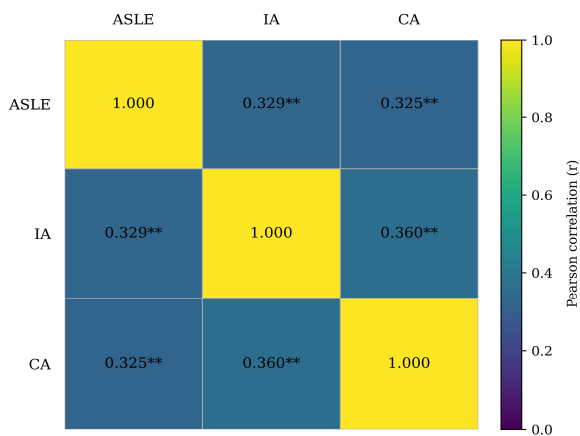


Figure 3. Heatmap of Pearson correlations among AI-Supported Learning Experience, Innovation Ability, and Career Adaptability. (Note. **Coefficients are significant at $p < 0.001$).

4.2.2. Confirmatory Factor Analysis

The confirmatory factor analysis (CFA) was conducted to evaluate the adequacy of the measurement model. The model demonstrated acceptable fit to the data (CFI = 0.94; TLI = 0.93; RMSEA = 0.052; and SRMR = 0.045). These results indicate that the observed indicators adequately represented the latent constructs of AI-Supported Learning Experience, innovation ability, and career adaptability, thereby supporting the adequacy of the measurement model for subsequent structural analysis.

4.2.3. Discriminant Validity

Discriminant validity was then assessed using the Fornell-Larcker criterion. As reported in Table 6, the square root of AVE for each construct exceeded its correlations with the other constructs. Specifically, the diagonal values were 0.787 for ASLE, 0.806 for innovation ability, and 0.775 for career adaptability, all of which were greater than the corresponding inter-construct correlations.

Table 6. Discriminant validity on the Fornell-Larcker criterion

Construct	ASLE	IA	CA
AI-Supported Learning Experience	0.787		
Innovation Ability	0.329	0.806	
Career Adaptability	0.325	0.360	0.775

4.2.4. Reliability and Convergent Validity

Internal consistency reliability was first assessed using Cronbach's alpha, while convergent validity was examined using standardized factor loadings, composite reliability (CR), and average variance extracted (AVE). In Table 7 all constructs exceeded commonly accepted thresholds for reliability and convergent validity. Cronbach's alpha values were 0.804 for ASLE, 0.836 for innovation ability, and 0.803 for career adaptability. Standardized factor loadings ranged from 0.685 to 0.786, CR values ranged from 0.803 to 0.836, and AVE values ranged from 0.505 to 0.561.

Table 7. Reliability and Convergent Validity of the Measurement Model

Construct	Items	Loading Factor	CR	AVE	Cronbach's Alpha
AI-Supported Learning Experience	ASLE1	0.725	0.804	0.507	0.804
	ASLE2	0.685			
	ASLE3	0.704			
	ASLE4	0.734			
Innovation Ability	IA1	0.714	0.836	0.561	0.836
	IA2	0.757			
	IA3	0.738			
	IA4	0.786			
Career Adaptability	CA1	0.714	0.803	0.505	0.803
	CA2	0.717			

Construct	Items	Loading Factor	CR	AVE	Cronbach's Alpha
	CA3	0.707			
	CA4	0.705			

4.3. Structural Model Assessments (Goodness of Fit)

The structural model was estimated to test the hypothesized direct relationships among ASLE, innovation ability, and career adaptability. In line with good SEM reporting practice, the fit indices for the structural model are reported separately from the CFA results. The structural model demonstrated excellent fit to the data, with $\chi^2/df = 1.04$, CFI = 0.999, TLI = 0.998, RMSEA = 0.010, and SRMR = 0.027 (Table 9). In addition, the chi-square statistic was $\chi^2 = 53.10$, $df = 51$, $p = 0.393$, indicating that the hypothesized structural model adequately represented the observed covariance structure. These fit indices indicate that the proposed model was highly consistent with the data and that the estimated structural relationships could be interpreted with confidence.

Table 8. Structural model fit indices

Fit Index	Value	Threshold	Interpretation
χ^2/df	1.04	< 3.00 or < 5.00	Excellent fit
CFI	0.999	> 0.90	Excellent fit

Fit Index	Value	Threshold	Interpretation
TLI	0.998	> 0.90	Excellent fit
RMSEA	0.010	< 0.08	Excellent fit
SRMR	0.027	< 0.08	Excellent fit

Note. $\chi^2 = 53.10$, $df = 51$, $p = 0.393$.

4.4. Structural Model and Hypothesis Assessments

The direct effects of the hypothesized model are reported in Table 10. First, AI-Supported Learning Experience had a positive and significant effect on innovation ability ($\beta = 0.329$, $SE = 0.047$, $t = 7.06$, $p < 0.001$, 95% CI [0.24, 0.41]), supporting H1. Second, AI-Supported Learning Experience had a positive and significant direct effect on career adaptability ($\beta = 0.231$, $SE = 0.047$, $t = 4.87$, $p < 0.001$, 95% CI [0.14, 0.32]), supporting H2. Third, innovation ability had a positive and significant effect on career adaptability ($\beta = 0.284$, $SE = 0.047$, $t = 5.98$, $p < 0.001$, 95% CI [0.19, 0.36]), supporting H3. These findings indicate that students who reported stronger AI-supported learning experiences also tended to report stronger innovation ability and greater career adaptability.

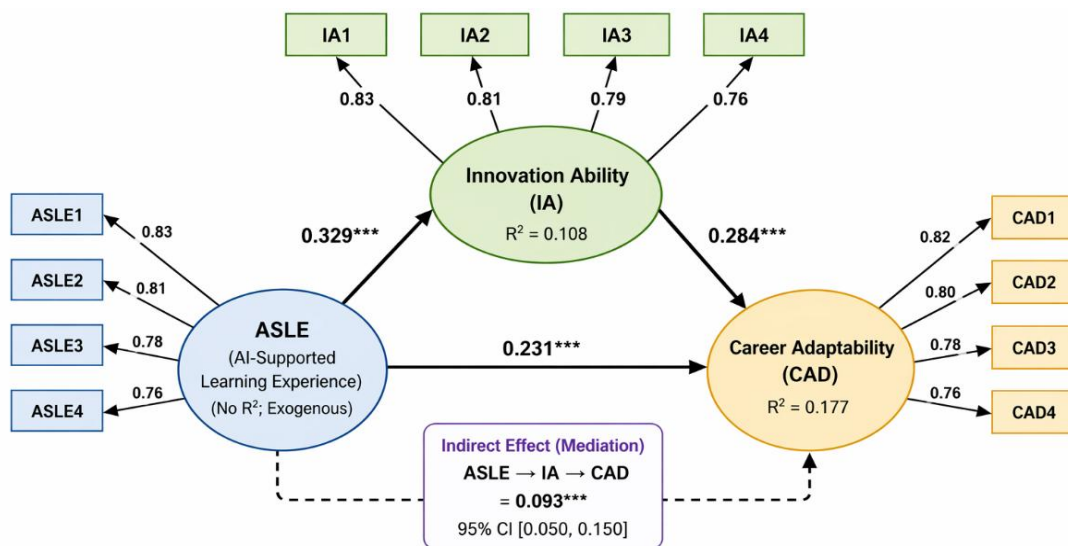


Figure 4. Final structural equation model showing the relationships among AI-Supported Learning Experience, Innovation Ability, and Career Adaptability (** $p < 0.001$).

Table 9. Structural Path Coefficients of the Hypothesized Model

Path	β	SE	t	p	95% CI	Decision
AI-Supported Learning Experience → Innovation Ability	0.329	0.047	7.06	< 0.001	[0.24; 0.41]	H1 Supported
AI-Supported Learning Experience → Career Adaptability	0.231	0.047	4.87	< 0.001	[0.14; 0.32]	H2 Supported
Innovation Ability → Career Adaptability	0.284	0.047	5.98	< 0.001	[0.19; 0.36]	H3 Supported

Note. β = standardized path coefficient; SE = standard error; CI = confidence interval. All hypothesized direct effects were positive and statistically significant.

Table 10. Mediation Effects of Innovation Ability in the Structural Model

Path	Direct Effect	Indirect Effect	Total Effect	Bootstrap SE	95% Bootstrap CI	Decision
AI-Supported Learning Experience → Career Adaptability	0.231	0.093	0.324	0.023	Direct: [0.14, 0.32]; Indirect: [0.05, 0.15]	Partial mediation

4.5. Mediation Analysis

The mediating role of innovation ability in the relationship between ASLE and career adaptability was examined using bootstrapping with 5,000 resamples. As reported in Table 12, the indirect effect of ASLE on career adaptability through innovation ability was 0.093, with a Bootstrap SE = 0.023 and a 95% bootstrap confidence interval of [0.05, 0.15]. Because the confidence interval did not include zero, the indirect effect was statistically significant. The direct effect of ASLE on career adaptability remained significant (0.231, 95% CI [0.14, 0.32]), and the total effect was 0.324. These results indicate that innovation ability partially mediates the relationship between AI-Supported Learning Experience and career adaptability, thereby supporting H4.

4.6. Explained Variance of Endogenous Constructs

The explanatory power of the structural model was assessed using the R^2 values of the endogenous constructs. As shown in Table 11, the model explained 10.8% of the variance in innovation ability and 17.7% of the variance in career adaptability. These values indicate modest explanatory power. In substantive terms, ASLE contributed meaningfully to innovation ability, while ASLE and innovation ability jointly explained a meaningful proportion of variance in career adaptability.

Table 11. Explained variance (R^2) of endogenous variables

Variable	R^2	Interpretation
Innovation Ability	0.108	Modest explanatory power
Career Adaptability	0.177	Modest explanatory power

5. DISCUSSION

This study has investigated the connections between AI-Supported Learning Experience, innovation ability, and career adaptability in university students and evaluated the mediation role of innovation ability. The findings not only confirmed the hypothesized positive relationships between ASLE and innovation ability and career adaptability but also indicated that innovation ability was a mediator between the ASLE and career adaptability relationship. Collectively, the results indicate that the developmental worth of AI-enhanced learning is not found in the availability of digital tools, but also the capacity-forming processes that the ecosystems can provoke.

These findings are in line with Social Cognitive Career Theory, which highlights the importance of learning experiences and perceived competence in influencing adaptive career resources. In this context, ASLE can be viewed as a kind of learning experience that reinforces the students with their ideologies concerning their capacity to resolve issues, experiment and react to the change. The results can also be compared to the Self-Determination Theory since AI-based learning settings can contribute to autonomy, competence, and engagement in case they are introduced in properly designed learning activities.

The outcome of the mediation is of particular importance since the ability to innovate has been recognized as a substantive explanatory mechanism instead of AI exposure being viewed as a sufficient factor. Practically, it can be argued that universities cannot expect that the implementation of AI tools will result in better career preparation. Rather, the learning design around such tools should be designed to help foster imaginative problem solving, experimentation, reflection, and transfer of knowledge to novel circumstances in an intentional way [68], [69].

5.1. AI-Supported Learning Experience and Innovation Ability

The first major finding is that ASLE positively predicts innovation ability. This result supports the interpretation that AI-supported learning environments can serve as pedagogical spaces that encourage exploration, idea generation, and flexible problem solving. In the present study, ASLE was conceptualized as students perceived exposure to AI-supported tools, activities, and learning support embedded in their courses. Such experiences plausibly create conditions for experimentation, iterative feedback, and engagement with complex tasks, all of which are relevant to innovation-oriented development.

This interpretation is consistent with prior literature showing that AI-integrated educational applications can both stimulate creativity and enrich academic engagement when they are embedded in meaningful learning tasks. Lin and Chen found that AI-integrated educational applications were associated with both opportunities and tensions for students' creativity and academic emotions, highlighting that AI can stimulate creative thinking while also constraining it if implemented rigidly. More broadly, recent systematic reviews conclude that AI-supported learning is most effective when integrated into interactive pedagogies, such as scaffolded feedback, project-based learning, and personalized

support, rather than treated as a stand-alone technical add-on.

A stronger synthesis with the innovation literature also helps sharpen this interpretation. Research on innovation competences in higher education shows that innovation-related student outcomes are typically reflected in creative problem solving, experimentation, transfer of knowledge, and exploratory engagement in authentic learning environments. These are highly consistent with the dimensions captured by the innovation ability construct in the present study. Thus, the current finding does not merely suggest that AI “improves creativity” in a broad sense; rather, it suggests that AI-supported learning may contribute to the specific higher-order capabilities that underlie innovation-oriented performance in higher education [56], [57].

At the same time, this result should not be interpreted as evidence that AI exposure automatically produces innovation. A more defensible interpretation is that AI appears beneficial when students experience it as part of an intellectually demanding and pedagogically meaningful learning process. Recent studies caution that AI can be a dual-edged educational force: it may expand idea generation and feedback, but it may also constrain originality, reduce deep engagement, or encourage dependence if instructional design is weak. Therefore, the present finding reinforces a pedagogical rather than a technological explanation: what matters is not only whether AI is available, but whether it is embedded in ways that support higher-order thinking [69], [70].

5.2. AI-Supported Learning Experience and Career Adaptability

The second major finding is that ASLE positively predicts career adaptability, suggesting that students who report stronger AI-supported learning experiences also feel more prepared to cope with career-related uncertainty, technological change, and evolving labor-market demands. This is an important contribution because much of the literature on AI in higher education has focused on adoption, literacy, and classroom-level outcomes. In contrast, the present study connects AI-supported learning to career adaptability, a psychosocial resource for managing vocational tasks, transitions, and work-related disruptions [11], [71].

This relationship is conceptually plausible for at least two reasons. First, AI-supported learning may familiarize students with emerging digital tools, AI-mediated workflows, and technology-rich problem environments, thereby making future workplace change feel more manageable. Second, such learning experiences may strengthen students’ confidence in dealing with novelty, ambiguity, and continuous adjustment, which are central features of career adaptability. Career construction theory and meta-analytic evidence consistently show that career adaptability is closely associated with adaptive resources

and responses such as planning, exploration, self-efficacy, and employability-related outcomes [72].

The present result also extends emerging work linking AI-related capabilities to employability and labor-market alignment. Recent evidence indicates that stronger AI skills are associated with higher perceived employability among university graduates, while broader higher education research shows growing pressure on universities to integrate AI and digital capabilities into curricula as part of employability development and curriculum relevance [6], [30], [70]. Against this backdrop, the current finding suggests that AI-supported learning may function as an early developmental context in which students begin to build adaptive readiness for a labor market increasingly shaped by AI and digital transformation.

An important conceptual distinction should be maintained here: ASLE is not identical to AI literacy. AI literacy refers more broadly to the knowledge, skills, ethical awareness, and critical understanding needed to engage responsibly with AI. In contrast, ASLE refers to students’ perceived learning experiences with AI-supported tools and activities. The current finding therefore, adds construct clarity by showing that experiential AI-supported learning, even apart from formal AI literacy instruction, may still relate positively to students’ adaptive career resources. This distinction is theoretically and practically important because it suggests that universities may strengthen career readiness not only through dedicated AI literacy curricula, but also through the quality of AI-mediated learning experiences embedded across courses [73], [74].

5.3. Innovation Ability as a Mediating Mechanism

The most theoretically significant finding of this study is the partial mediating role of innovation ability in the relationship between ASLE and career adaptability. The significant indirect effect, together with the remaining significant direct effect, indicates that AI-supported learning contributes to students’ career adaptability both directly and indirectly through the development of innovation-oriented capabilities. This suggests that the educational value of AI-supported learning lies not only in technological exposure but also in its capacity to strengthen personal resources that help students manage change, uncertainty, and future career transitions. Such an interpretation is consistent with career construction theory, which conceptualizes career adaptability as a psychosocial resource for coping with vocational tasks, transitions, and work-related challenges, and with the broader career adaptation model linking adaptive traits, adaptability resources, and adaptation outcomes [11], [71].

This mediation finding therefore, offers a more nuanced explanation than a direct-effects-only model. Students who experience AI-supported learning as interactive, exploratory, and competence-enhancing may

become more capable of generating ideas, testing alternatives, and applying knowledge in unfamiliar situations. These innovation-oriented capabilities can, in turn, strengthen their readiness and confidence in dealing with future career transitions. Prior evidence also indicates that innovation capability is positively associated with employability and works together with self-efficacy and social adaptability in supporting students' career-related development. In this sense, innovation ability can be understood as a developmental bridge between learning experience and adaptive career readiness [75].

The result is also theoretically aligned with the career adaptability literature, which emphasizes that adaptive career outcomes are supported by resources and responses such as planning, exploration, confidence, and self-efficacy. Meta-analytic evidence shows that career adaptability is meaningfully associated with adaptivity, adapting responses, and adaptation results, while related work further suggests that adaptability resources mediate the influence of broader personal dispositions on career-specific behaviors. This makes the innovation ability conceptually relevant as an adaptive resource, because creative problem solving, experimentation, and flexible thinking are highly valuable in uncertain and changing career environments [76].

From an educational perspective, this finding suggests that universities should not assume that AI use alone will automatically improve employability or adaptive readiness. Rather, AI becomes educationally meaningful when it is embedded in pedagogically sound learning processes that cultivate durable capabilities, rather than being used merely as a shortcut or passive automation tool. Recent reviews of AI in higher education similarly conclude that its benefits depend strongly on pedagogical design, contextual integration, and educational purpose [33].

5.4. Alternative Explanations and Boundary Conditions

A stronger interpretation of these findings requires consideration of plausible alternative explanations and boundary conditions. First, ASLE may capture not only the effects of AI-supported learning itself, but also broader institutional qualities such as digital readiness, instructional quality, pedagogical innovation, and academic support. Universities that implement AI effectively are often those with stronger educational ecosystems overall. Thus, part of the observed relationship may reflect the contribution of institutional context rather than AI exposure alone. This interpretation aligns with review studies showing that the educational impact of AI depends strongly on pedagogical integration, contextual design, and institutional readiness [1], [2].

Second, innovation ability is unlikely to be the only mechanism linking ASLE to career adaptability. The relatively modest explanatory power of the model ($R^2 = 0.108$ for innovation ability; $R^2 = 0.177$ for career

adaptability) suggests that substantial variance remains unexplained. Prior research indicates that career adaptability is also shaped by other personal and contextual resources, including self-efficacy, career identity, social support, and adaptive responses to career challenges [77]-[79]. Therefore, the present findings should be interpreted as identifying an important, but partial, explanatory pathway.

Third, the high mean score for career adaptability ($M = 4.35$) may indicate an upper-end response tendency or partial ceiling effect. Restricted variance in the outcome variable may have influenced the magnitude of the observed associations. In addition, because the study relies on single-source self-report data, common method variance cannot be fully ruled out. This limitation does not invalidate the findings, but it does suggest the need for more heterogeneous samples, longitudinal designs, and multi-method approaches in future research [77].

Fourth, recent literature also warns that AI in higher education may generate countervailing risks, including overreliance, reduced independent thinking, reliability concerns, and ethical problems when AI is used as a substitute rather than a learning support [1], [80], [81]. For this reason, the present results should not be interpreted as support for uncritical AI expansion. A more defensible conclusion is that AI-supported learning can be beneficial when it is pedagogically well-designed and institutionally supported. However, its effects may be weaker or even counterproductive when implementation is poorly managed.

5.5. Theoretical and practical implications

Theoretically, this study contributes by integrating innovation ability and career adaptability within a single explanatory model of AI-Supported Learning Experience. Prior work has often examined AI adoption, creativity, engagement, employability, or AI literacy separately. By contrast, the present study positions ASLE as a developmental learning context. It shows that innovation ability is not merely a parallel outcome, but also a mechanism through which AI-supported learning relates to adaptive career readiness. This provides a more coherent account of how AI-supported educational experiences may shape student development beyond immediate academic task performance.

Practically, the findings imply that higher education institutions should move beyond simply exposing students to AI tools. If innovation ability partly explains the relationship between ASLE and career adaptability, then AI-related teaching should be designed to include authentic problem solving, iterative inquiry, interdisciplinary tasks, experimentation, and explicit reflection on how AI-related learning connects to future work. Recent literature similarly emphasizes that successful AI integration in higher education requires not only access to tools but also training, ethical guidance,

pedagogical alignment, and learning designs that preserve critical thinking and student agency.

5.6. Limitations and Future Research

This study has several limitations. First, the cross-sectional design does not allow causal inferences to be drawn. Although the findings indicate significant associations among the constructs, longitudinal research would be valuable for examining how these relationships develop over time. Second, the study relied on self-reported data, which may introduce common method bias and social desirability bias despite the use of anonymity and voluntary participation procedures. Third, the sample was limited to undergraduate students from four universities in China, which restricts the generalizability of the findings to other institutional and national contexts. In addition, because the archived final analytical dataset did not retain institution-level identifiers or program-level codes, the study could not report university-wise respondent counts or major-wise sampling distributions retrospectively, which limits the granularity of contextual reporting. Future studies should therefore include more diverse samples and incorporate additional explanatory variables such as self-efficacy, learning motivation, digital competence, instructional quality, and institutional support.

6. CONCLUSION

This study shows that AI-Supported Learning Experience (ASLE) is positively associated with both innovation ability and career adaptability among university students. ASLE significantly predicted innovation ability and career adaptability, while innovation ability also significantly predicted career adaptability. In addition, innovation ability partially mediated the relationship between ASLE and career adaptability, indicating that the contribution of AI-supported learning extends beyond direct technological exposure to include the development of innovation-oriented capability. These findings support the conceptual value of ASLE as a distinct construct reflecting students' actual AI-mediated learning experiences rather than formal AI curriculum exposure alone.

The study extends the higher education literature by integrating innovation ability and career adaptability within a single explanatory model of AI-supported learning. However, the findings should be interpreted with caution due to the cross-sectional design, self-reported data, and the focus on four universities in China. Rather than suggesting that AI exposure alone is sufficient to prepare students for future work, the results indicate that well-designed AI-supported learning environments may help universities foster more innovative and career-adaptive graduates when AI is embedded in pedagogical processes that promote inquiry, experimentation, problem solving, and knowledge transfer.

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CONFLICTS OF INTEREST

The authors declare that no conflicts of interest are associated with this study. All aspects of the research were conducted with the utmost integrity and transparency.

DATA AVAILABILITY

The datasets utilized and analyzed during this research are available from the corresponding author upon reasonable request.

ETHICAL STATEMENTS

The authors confirm that the study complied with all applicable local laws, ethical standards, and institutional guidelines, including obtaining approval from relevant ethics committees.

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REFERENCES

- [1] M. Bond et al., "A meta systematic review of artificial intelligence in higher education: a call for increased ethics, collaboration, and rigour," *Int. J. Educ. Technol. High. Educ.*, vol. 21, no. 1, p. 4, 2024, <https://doi.org/10.1186/s41239-023-00436-z>
- [2] S. Wang, F. Wang, Z. Zhu, J. Wang, T. Tran, and Z. Du, "Artificial intelligence in education: A systematic literature review," *Expert Syst. Appl.*, vol. 252, no. Part A, p. 124167, 2024, <https://doi.org/10.1016/j.eswa.2024.124167>
- [3] H. Crompton and D. Burke, "Artificial intelligence in higher education: the state of the field," *Int. J. Educ. Technol. High. Educ.*, vol. 20, no. 1, pp. 1-22, 2023, <https://doi.org/10.1186/s41239-023-00392-8>
- [4] J. Southworth et al., "Developing a model for AI Across the curriculum: Transforming the higher education landscape via innovation in AI literacy," *Comput. Educ. Artif. Intell.*, vol. 4, p. 100127, 2023, <https://doi.org/10.1016/j.caeai.2023.100127>
- [5] C. K. Y. Chan, "A comprehensive AI policy education framework for university teaching and learning," *Int. J. Educ. Technol. High. Educ.*, vol. 20, no. 1, p. 38, 2023, <https://doi.org/10.1186/s41239-023-00408-3>
- [6] B. N. Abbasi, Y. Wu, and Z. Luo, "Exploring the impact of artificial intelligence on curriculum development in global higher education institutions," *Educ. Inf. Technol.*, vol. 30, no. 1, pp. 547-581, 2025, <https://doi.org/10.1007/s10639-024-13113-z>
- [7] B. Memarian and T. Doleck, "Teaching and learning artificial intelligence: Insights from the literature," *Educ. Inf. Technol.*, vol. 29, no. 16, pp. 21523-21546, 2024, <https://doi.org/10.1007/s10639-024-12679-y>
- [8] B. L. Muna, S. Sudianto, and M. L. L. Usman, "Siakif-Bots: Gemini Ai for Academic Service Chatbots," *J. Appl. Eng. Technol. Sci.*, vol. 6, no. 2, pp. 1237-1253, 2025, <https://doi.org/10.37385/jaets.v6i2.6728>
- [9] U. A. A. Rauf, M. M. Deli, and N. Husin, "From Exclusion To Empowerment: Redesigning E-Learning To Mitigate Risks

- for Disabled Students,” *J. Appl. Eng. Technol. Sci.*, vol. 7, no. 1, pp. 129–143, 2025, <https://doi.org/10.37385/jaets.v7i1.7608>
- [10] O. Zawacki-Richter, V. I. Marín, M. Bond, and F. Gouverneur, “Systematic review of research on artificial intelligence applications in higher education – where are the educators?,” *Int. J. Educ. Technol. High. Educ.*, vol. 16, no. 1, p. 39, 2019, <https://doi.org/10.1186/s41239-019-0171-0>
- [11] M. L. Savickas and E. J. Porfeli, “Career Adapt-Abilities Scale: Construction, reliability, and measurement equivalence across 13 countries,” *J. Vocat. Behav.*, vol. 80, no. 3, pp. 661–673, 2012, <https://doi.org/10.1016/j.jvb.2012.01.011>
- [12] M. Haenggli and A. Hirschi, “Career adaptability and career success in the context of a broader career resources framework,” *J. Vocat. Behav.*, vol. 119, p. 103414, 2020, <https://doi.org/10.1016/j.jvb.2020.103414>
- [13] J. Rossier, M. C. Ginevra, G. Bollmann, and L. Nota, “The importance of career adaptability, career resilience, and employability in designing a successful life,” in *Psychology of Career Adaptability, Employability and Resilience*, Springer, 2017, pp. 65–82. https://doi.org/10.1007/978-3-319-66954-0_5
- [14] M. E. Duarte, J. T. da Silva, and M. P. Paixão, “Career adaptability, employability, and career resilience in managing transitions,” in *Psychology of Career Adaptability, Employability and Resilience*, Springer, 2017, pp. 241–261. https://doi.org/10.1007/978-3-319-66954-0_15
- [15] F. Ouyang and P. Jiao, “Artificial intelligence in education: The three paradigms,” *Comput. Educ. Artif. Intell.*, vol. 2, p. 100020, 2021, <https://doi.org/10.1016/j.caeai.2021.100020>
- [16] H. Lin and Q. Chen, “Artificial intelligence (AI) -integrated educational applications and college students’ creativity and academic emotions: students and teachers’ perceptions and attitudes,” *BMC Psychol.*, vol. 12, no. 1, p. 487, 2024, <https://doi.org/10.1186/s40359-024-01979-0>
- [17] H.-B. Sheu and L. Phrasavath, “Social cognitive career theory,” *Contemp. Theor. Career Dev.*, vol. 4, no. 1, pp. 47–60, 2019, <https://doi.org/10.4324/9781315276175-6>
- [18] R. M. Ryan and E. L. Deci, “Self-determination theory and the facilitation of intrinsic motivation, social development, and well-being,” *Am. Psychol.*, vol. 55, no. 1, pp. 68–78, 2000, <https://doi.org/10.1037/0003-066X.55.1.68>
- [19] R. M. Ryan and E. L. Deci, “Intrinsic and Extrinsic Motivations: Classic Definitions and New Directions,” *Contemp. Educ. Psychol.*, vol. 25, no. 1, pp. 54–67, 2000, <https://doi.org/10.1006/ceps.1999.1020>
- [20] E. L. Deci and R. M. Ryan, “The ‘what’ and ‘why’ of goal pursuits: Human needs and the self-determination of behavior,” *Psychol. Inq.*, vol. 11, no. 4, pp. 227–268, 2000, https://doi.org/10.1207/S15327965PLI1104_01
- [21] G. M. Idroes et al., “Student Perspectives on the Role of Artificial Intelligence in Education: A Survey-Based Analysis,” *J. Educ. Manag. Learn.*, vol. 1, no. 1, pp. 8–15, 2023, <https://doi.org/10.60084/jeml.v1i1.58>
- [22] F. Amastini, D. K. S. Sekarhati, and M. Puspitasari, “Advancing Adaptive and Personalized E-Learning Systems: A Systematic Literature Review,” *Adv. Sustain. Sci. Eng. Technol.*, vol. 7, no. 2, 2025, <https://doi.org/10.26877/m82zg802>
- [23] F. Ouyang, L. Zheng, and P. Jiao, “Artificial intelligence in online higher education: A systematic review of empirical research from 2011 to 2020,” *Educ. Inf. Technol.*, vol. 27, no. 6, pp. 7893–7925, 2022, <https://doi.org/10.1007/s10639-022-10925-9>
- [24] M. E. Dogan, T. Goru Dogan, and A. Bozkurt, “The Use of Artificial Intelligence (AI) in Online Learning and Distance Education Processes: A Systematic Review of Empirical Studies,” *Appl. Sci.*, vol. 13, no. 5, p. 3056, 2023, <https://doi.org/10.3390/app13053056>
- [25] M. D. Adewale, A. Azeta, A. Abayomi-Alli, and A. Sambo-Magaji, “Impact of artificial intelligence adoption on students’ academic performance in open and distance learning: A systematic literature review,” *Heliyon*, vol. 10, no. 22, 2024, <https://doi.org/10.1016/j.heliyon.2024.e40025>
- [26] Ramesh C. Sharma, A. Bozkurt, and Paul Kawachi, “The Landscape of Artificial Intelligence in Open, Online and Distance Education: Promises and Concerns,” *Asian J. Distance Educ.*, vol. 14, no. 2, pp. 497–514, 2019.
- [27] Í. M. Oliveira and C. Marques, “The Role of Career Adaptability and Academic Engagement in College Student’s Life Satisfaction,” *Int. J. Environ. Res. Public Health*, vol. 21, no. 5, p. 596, 2024, <https://doi.org/10.3390/ijerph21050596>
- [28] M. Fang, R. Pan, R. Ding, Z. Hou, and D. Wang, “Effect of proactive personality on career adaptability of higher vocational college students: the mediating role of college experience,” *Front. Psychol.*, vol. 15, p. 1333677, 2024, <https://doi.org/10.3389/fpsyg.2024.1333677>
- [29] C. Pang, R. Xie, N. Kang, and Z. Hu, “The Impact of Career Education Participation on Academic Self-Efficacy: The Sequential Mediating Role of Career Adaptability and Learning Engagement,” *Behav. Sci. (Basel)*, vol. 15, no. 2, p. 174, 2025, <https://doi.org/10.3390/bs15020174>
- [30] H. C. Portocarrero Ramos et al., “Artificial intelligence skills and their impact on the employability of university graduates,” *Front. Artif. Intell.*, vol. 8, p. 1629320, 2025, <https://doi.org/10.3389/frai.2025.1629320>
- [31] M. M. Asad and K. Anwar, “Influence of artificial intelligence on students’ career competencies and career resources: a global perspective,” *Int. J. Inf. Learn. Technol.*, vol. 42, no. 4, pp. 366–391, 2025, <https://doi.org/10.1108/IJILT-05-2024-0091>
- [32] X. Wang, S. Zhao, X. Xu, H. Zhang, and V. N. L. Lei, “AI adoption in Chinese universities: Insights, challenges, and opportunities from academic leaders,” *Acta Psychol. (Amst)*, vol. 258, p. 105160, 2025, <https://doi.org/10.1016/j.actpsy.2025.105160>
- [33] Y. Zhang, M. Zhang, L. Wu, and J. Li, “Digital Transition Framework for Higher Education in AI-Assisted Engineering Teaching: Challenge, Strategy, and Initiatives in China,” *Sci. Educ.*, vol. 34, no. 2, pp. 933–954, 2025, <https://doi.org/10.1007/s11191-024-00575-3>
- [34] Y. Huang, J. Zhang, Y. Xu, and Y. Bu, “How can digital innovation capabilities of Chinese college students be cultivated?,” *Int. J. Manag. Educ.*, vol. 22, no. 3, p. 101085, 2024, <https://doi.org/10.1016/j.ijme.2024.101085>
- [35] Y. Ma and D. Bennett, “Analyzing predictors of perceived graduate employability from sufficiency and necessity perspectives,” *High. Educ.*, vol. 88, no. 6, pp. 2375–2397, 2024, <https://doi.org/10.1007/s10734-024-01221-1>
- [36] Ministry of Education of the People’s Republic of China, “MOE outlines 2025 national strategy for digital education,”

- Ministry of Education of the People's Republic of China, 2025.
http://en.moe.gov.cn/news/press_releases/202504/t20250403_1186060.html
- [37] O. Zawacki-Richter, V. I. Marín, M. Bond, and F. Gouverneur, "Systematic review of research on artificial intelligence applications in higher education - where are the educators?," *Int. J. Educ. Technol. High. Educ.*, vol. 16, no. 1, pp. 1-27, 2019, <https://doi.org/10.1186/s41239-019-0171-0>
- [38] T. Bates, C. Cobo, O. Mariño, and S. Wheeler, "Can artificial intelligence transform higher education?," *Int. J. Educ. Technol. High. Educ.*, vol. 17, no. 1, p. 42, 2020, <https://doi.org/10.1186/s41239-020-00218-x>
- [39] L. Kuka, C. Hörmann, and B. Sabitzer, "Teaching and Learning with AI in Higher Education: A Scoping Review," *Lect. Notes Networks Syst.*, vol. 456, pp. 551-571, 2022, https://doi.org/10.1007/978-3-031-04286-7_26
- [40] O. Noroozi, M. Khalil, and S. K. Banihashem, "Artificial Intelligence in higher education: Impact depends on support, pedagogy, human agency, and purpose," *Innovations in Education and Teaching International*, vol. 62, no. 5. Taylor & Francis, pp. 1425-1430, 2025. <https://doi.org/10.1080/14703297.2025.2539579>
- [41] A. Katalinic, V. Slavuj, and D. Jaksic, "Artificial Intelligence in Online Education: A Systematic Review of Its Impact on Learner Engagement and Satisfaction," in *Education Sciences*, 2026, vol. 16, no. 3, p. 1648661. <https://doi.org/10.3390/educsci16030389>
- [42] D. Y. Long, S. Wang, S. Md Rashid, and X. T. Lu, "Artificial intelligence in higher education: a systematic review of its impact on student engagement and the mediating role of teaching methods," in *Frontiers in Education*, 2026, vol. 10, p. 1648661. <https://doi.org/10.3389/feduc.2025.1648661>
- [43] X. Li, X. Weng, and Q. Qu, "Technology-enhanced creativity and entrepreneurship curricula in higher education: Systematic review from the perspective of self-determination theory," *Think. Ski. Creat.*, p. 102144, 2026, <https://doi.org/10.1016/j.tsc.2026.102144>
- [44] S. Alateyyat and M. Soltan, "Utilizing Artificial Intelligence in Higher Education: A Systematic Review," in *2024 ASU International Conference in Emerging Technologies for Sustainability and Intelligent Systems, ICETSIS 2024*, 2024, pp. 371-374. <https://doi.org/10.1109/ICETSIS61505.2024.10459629>
- [45] I. M. Castillo-Martínez, D. Flores-Bueno, S. M. Gómez-Puente, and V. O. Vite-León, "AI in higher education: A systematic literature review," in *Frontiers in Education*, 2024, vol. 9, p. 1391485. <https://doi.org/10.3389/feduc.2024.1391485>
- [46] R. W. Lent, S. D. Brown, and G. Hackett, "Toward a Unifying Social Cognitive Theory of Career and Academic Interest, Choice, and Performance," *J. Vocat. Behav.*, vol. 45, no. 1, pp. 79-122, 1994, <https://doi.org/10.1006/jvbe.1994.1027>
- [47] R. W. Lent, G. W. Ireland, L. T. Penn, T. R. Morris, and R. Sappington, "Sources of self-efficacy and outcome expectations for career exploration and decision-making: A test of the social cognitive model of career self-management," *J. Vocat. Behav.*, vol. 99, pp. 107-117, 2017, <https://doi.org/10.1016/j.jvb.2017.01.002>
- [48] C.-Y. Huang, S.-J. Lou, Y.-M. Cheng, and C.-C. Chung, "Research on teaching a welding implementation course assisted by sustainable virtual reality technology," *Sustain.*, vol. 12, no. 23, pp. 1-21, 2020, <https://doi.org/10.3390/su122310044>
- [49] N. Q. T. Vo, P. K. T. Tran, and D. H. T. Nguyen, "How experiential learning and AI readiness foster career adaptation in hospitality and tourism education," *J. Tour. Futur.*, pp. 1-21, 2026, <https://doi.org/10.1108/JTF-10-2025-0312>
- [50] K. S. S. S. Ray, D. M. Mahapatra, B. L. Rout, and Z. H. Shaikh, "AI and the Future of Foundational Learning: How Can AI Support Lifelong Learning and Prepare Learners for the Evolving Global Workforce?," in *Cases on AI-Driven Talent Economy and Human Capital*, IGI Global Scientific Publishing, 2026, pp. 1-30. <https://doi.org/10.4018/979-8-3373-3867-5.ch001>
- [51] X. Ye, W. Zhang, Y. Zhou, X. Li, and Q. Zhou, "Improving students' programming performance: an integrated mind mapping and generative AI chatbot learning approach," *Humanit. Soc. Sci. Commun.*, vol. 12, no. 1, pp. 1-13, 2025, <https://doi.org/10.1057/s41599-025-04846-4>
- [52] G. W. Cheung, H. D. Cooper-Thomas, R. S. Lau, and L. C. Wang, "Reporting reliability, convergent and discriminant validity with structural equation modeling: A review and best-practice recommendations," *Asia Pacific J. Manag.*, vol. 41, no. 2, pp. 745-783, 2024, <https://doi.org/10.1007/s10490-023-09871-y>
- [53] C. Fornell and D. F. Larcker, "Evaluating Structural Equation Models with Unobservable Variables and Measurement Error," *J. Mark. Res.*, vol. 18, no. 1, p. 39, 1981, <https://doi.org/10.2307/3151312>
- [54] F. Balabdaoui, N. Dittmann-Domenichini, H. Grosse, C. Schlienger, and G. Kortemeyer, "A survey on students' use of AI at a technical university," *Discov. Educ.*, vol. 3, no. 1, p. 51, 2024, <https://doi.org/10.1007/s44217-024-00136-4>
- [55] J. Heil, D. Ifenthaler, M. Cooper, M. L. Mascia, R. Conti, and M. P. Penna, "Students' perceived impact of GenAI tools on learning and assessment in higher education: the role of individual AI competence," *Smart Learn. Environ.*, vol. 12, no. 1, p. 37, 2025, <https://doi.org/10.1186/s40561-025-00395-0>
- [56] B. S. Selznick and M. J. Mayhew, "Measuring Undergraduates' Innovation Capacities," *Res. High. Educ.*, vol. 59, no. 6, pp. 744-764, 2018, <https://doi.org/10.1007/s11162-017-9486-7>
- [57] M. Keinänen, J. Ursin, and K. Nissinen, "How to measure students' innovation competences in higher education: Evaluation of an assessment tool in authentic learning environments," *Stud. Educ. Eval.*, vol. 58, pp. 30-36, 2018, <https://doi.org/10.1016/j.stueduc.2018.05.007>
- [58] M. M. Keinänen and L. Kairisto-Mertanen, "Researching learning environments and students' innovation competences," *Educ. Train.*, vol. 61, no. 1, pp. 17-30, 2019, <https://doi.org/10.1108/ET-03-2018-0064>
- [59] C. Maggiori, J. Rossier, and M. L. Savickas, "Career adaptabilities scale-short form (CAAS-SF) construction and validation," *J. career Assess.*, vol. 25, no. 2, pp. 312-325, 2017.
- [60] H. Yu, Y. Dai, X. Guan, and W. Wang, "Career Adapt-Abilities Scale-Short Form (CAAS-SF): Validation Across Three Different Samples in the Chinese Context," *J. Career Assess.*, vol. 28, no. 2, pp. 219-240, 2020, <https://doi.org/10.1177/1069072719850575>

- [61] J. E. Collier, *Applied structural equation modeling using amos: Basic to advanced techniques*. Routledge, 2020. <https://doi.org/10.4324/9781003018414>
- [62] J. F. Hair, M. C. Howard, and C. Nitzl, "Assessing measurement model quality in PLS-SEM using confirmatory composite analysis," *J. Bus. Res.*, vol. 109, pp. 101–110, 2020, <https://doi.org/10.1016/j.jbusres.2019.11.069>
- [63] P. M. Bentler and D. G. Bonett, "Significance tests and goodness of fit in the analysis of covariance structures," *Psychol. Bull.*, vol. 88, no. 3, pp. 588–606, 1980, <https://doi.org/10.1037/0033-2909.88.3.588>
- [64] S. Mulaik, "There is a place for approximate fit in structural equation modelling," *Pers. Individ. Dif.*, vol. 42, no. 5, pp. 883–891, 2007, <https://doi.org/10.1016/j.paid.2006.10.024>
- [65] H. W. Marsh, K. T. Hau, and D. Grayson, "Goodness of fit in structural equation models," *Contemp. Psychom. A Festschrift Roderick P. McDonald*, pp. 276–335, 2013, <https://doi.org/10.4324/9781410612977>
- [66] R. E. Schumacker and R. G. Lomax, *A Beginner's Guide to Structural Equation Modeling*, 3rd ed. Mahwah, NJ: Lawrence Erlbaum Associates, 2015. <https://doi.org/10.4324/9781315749105>
- [67] R. B. Kline, *Principles and practice of structural equation modeling*. Guilford publications, 2023.
- [68] L. Y. Tan, S. Hu, D. J. Yeo, and K. H. Cheong, "Artificial intelligence-enabled adaptive learning platforms: A review," *Comput. Educ. Artif. Intell.*, vol. 9, p. 100429, 2025, <https://doi.org/10.1016/j.caeai.2025.100429>
- [69] I. Gligorea, M. Cioca, R. Oancea, A. T. Gorski, H. Gorski, and P. Tudorache, "Adaptive Learning Using Artificial Intelligence in e-Learning: A Literature Review," *Educ. Sci.*, vol. 13, no. 12, p. 1216, 2023, <https://doi.org/10.3390/educsci13121216>
- [70] D. A. Schmidt, B. Alboloushi, A. Thomas, and R. Magalhaes, "Integrating artificial intelligence in higher education: perceptions, challenges, and strategies for academic innovation," *Comput. Educ. Open*, vol. 9, p. 100274, 2025, <https://doi.org/10.1016/j.caeo.2025.100274>
- [71] C. W. Rudolph, K. N. Lavigne, and H. Zacher, "Career adaptability: A meta-analysis of relationships with measures of adaptivity, adapting responses, and adaptation results," *J. Vocat. Behav.*, vol. 98, pp. 17–34, 2017, <https://doi.org/10.1016/j.jvb.2016.09.002>
- [72] M. L. Savickas, "The theory and practice of career construction," *Career Couns.*, pp. 192–202, 2020, <https://doi.org/10.4324/9781315693590-26>
- [73] S. C. Kong, M. Y. W. Cheung, and O. Tsang, "Developing an artificial intelligence literacy framework: Evaluation of a literacy course for senior secondary students using a project-based learning approach," *Comput. Educ. Artif. Intell.*, vol. 6, p. 100214, 2024, <https://doi.org/10.1016/j.caeai.2024.100214>
- [74] D. T. K. Ng, J. Su, J. K. L. Leung, and S. K. W. Chu, "Artificial intelligence (AI) literacy education in secondary schools: a review," *Interact. Learn. Environ.*, vol. 32, no. 10, pp. 6204–6224, 2024, <https://doi.org/10.1080/10494820.2023.2255228>
- [75] X. Li, R. Pu, and H. Liao, "The impacts of innovation capability and social adaptability on undergraduates' employability: The role of self-efficacy," *Front. Psychol.*, vol. 13, p. 954828, 2022, <https://doi.org/10.3389/fpsyg.2022.954828>
- [76] A. Hirschi, A. Herrmann, and A. C. Keller, "Career adaptivity, adaptability, and adapting: A conceptual and empirical investigation," *J. Vocat. Behav.*, vol. 87, pp. 1–10, 2015, <https://doi.org/10.1016/j.jvb.2014.11.008>
- [77] B. Cooper, N. Eva, F. Zarea Fazlelahi, A. Newman, A. Lee, and M. Obschonka, "Addressing common method variance and endogeneity in vocational behavior research: A review of the literature and suggestions for future research," *J. Vocat. Behav.*, vol. 121, p. 103472, 2020, <https://doi.org/10.1016/j.jvb.2020.103472>
- [78] R. M. Agoes Salim, M. R. Istiasih, N. A. Rumalutur, and D. D. Biondi Situmorang, "The role of career decision self-efficacy as a mediator of peer support on students' career adaptability," *Heliyon*, vol. 9, no. 4, 2023, <https://doi.org/10.1016/j.heliyon.2023.e14911>
- [79] J. Soares and M. do C. Taveira, "Career adaptation in higher education: a study with non-working and working students," in *Frontiers in Education*, 2024, vol. 9, p. 1314663. <https://doi.org/10.3389/feduc.2024.1314663>
- [80] UNESCO, *AI and the future of education: Disruptions, dilemmas and directions*. Paris: UNESCO, 2025. <https://doi.org/10.54675/keck1261>
- [81] R. R. Wang, "Not just a plus: rethinking the 'AI + Education' illusion," *AI Soc.*, vol. 41, no. 1, pp. 475–476, 2025, <https://doi.org/10.1007/s00146-025-02458-9>