

Beyond AI substitution and cultivation of entrepreneurial competencies: a mediation framework based on the SOR model

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Tao Xu

School of Innovation and Entrepreneurship, Tongji University, Shanghai, China

Ying Meng

School of Public Affairs, Zhejiang Shuren University, Hangzhou, China

Feng Guo

School of Innovation and Entrepreneurship, Zhejiang Shuren University, Hangzhou, China

Nan Luo

Office of Research and Social Services, Zhejiang Shuren University, Hangzhou, China, and

Yanxiang Chen

School of Innovation and Entrepreneurship, Zhejiang Shuren University, Hangzhou, China

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Abstract

Purpose – In the era of human–AI symbiosis, artificial intelligence (AI) is increasingly reshaping cognition, knowledge production and labor structures. These transformations, in turn, place growing pressure on higher education institutions to reform entrepreneurship education (EE). This study aims to examine how AI-enabled EE influences students’ entrepreneurial competencies by uncovering the underlying psychological mechanisms that remain resistant to AI substitution.

Design/methodology/approach – Grounded in the Stimulus–Organism–Response (SOR) model, this study explores how AI-enabled EE influences university students’ entrepreneurial competencies. This study conceptualized “AI adoption in higher education (AAHE)” in “entrepreneurship education (EE)” as the stimulus (S), “perceived usefulness (PU)” and “entrepreneurial self-efficacy (ESE)” as organismic states (O) and “entrepreneurial competency (EC)” as the response (R). A sample of 558 undergraduates from Shanghai and Zhejiang, China’s AI hub, was surveyed, and hypotheses were tested by Structural Equation Modeling.

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Findings – The empirical results showed AAHE positively predicted EE; AAHE and EE both boosted PU and ESE; and PU and ESE mediated the path to EC. These findings highlight the critical role of psychological mechanisms in translating AI integration into competencies development.

Originality/value – This study makes two key contributions: theoretically, it extends the application of the SOR model to AI-enabled EE and clarifies the mediating mechanisms of PU and ESE; practically, this research provides guidance for higher education institutions to cultivate students' entrepreneurial competencies by optimizing AI integration.

Keywords Artificial intelligence, Entrepreneurship education, S-O-R model, Entrepreneurial competency

Paper type Research paper

1. Introduction

The unprecedented technological revolution led by artificial intelligence (AI) is bringing the world into a human–AI symbiosis era. With the ongoing iteration and upgrading of AI technologies and applications, it continues to inject innovative momentum into each sector of society, profoundly transforming existing models and opening up unprecedented strategic opportunities for future development (Usman *et al.*, 2024). Meanwhile, with the evolution of AI, the occupational structure and entrepreneurial practices are being reshaped, new positions are constantly emerging and traditional positions are disappearing, being displaced or facing the need for skill updates (Fossen and Sorgner, 2021; Uriarte *et al.*, 2025). Besides, advanced computational analysis and predictive modeling have revolutionized how entrepreneurs interpret market trends, make informed decisions and forecast future developments (Koumbarakis and Volery, 2023; Omorede *et al.*, 2025), with machine learning algorithms based on large data sets helping entrepreneurs gain a deeper understanding of consumer behavior, identify new market trends and make more accurate predictions (Abakpa and Dvouléty, 2025; Giuggioli and Pellegrini, 2023). Conclusively, it is demonstrating a transformative driving force in entrepreneurial activities by providing fresh insights into market opportunities, enhancing strategic decision-making, promoting the refinement of market strategies, realizing intelligent automation of corporate operational processes and further stimulating innovation potential (Haleem *et al.*, 2022; Kizgin *et al.*, 2025; Wadhwa and Bansal, 2024). To catch up with economic transitions, industry needs and occupational changes driven by the broad adoption of AI, it is particularly urgent to leverage AI to transform the existing model of entrepreneurship education (EE) and to explore the paths for enhancing students' competencies.

From the perspective of the essence of education, the importance of entrepreneurial competencies has become increasingly prominent after the intervention of AI. AI can easily learn, imitate and even surpass knowledge-level content; however, human entrepreneurial competencies – including creativity, judgment, cooperation, leadership and critical thinking – is the core of literacy for an entrepreneur and “what makes us human” that AI cannot replace, enabling students to demonstrate their unique human value and agency in the intelligent era (Somia and Vecchiarini, 2024). Hence, higher education institutions accelerate the reformation of the current education system and curriculum content to cope with the rising needs of EE to cultivate students' literacy (Basheer, 2023). Accordingly, governments worldwide have formulated policies and measures to deeply embed AI into education and entrepreneurship systems to keep up with the requirements of technological advances. For instance, China's “Outline of the National Plan for Building a Strong Education Nation (2024–2035)” (The State Council of the People's Republic of China, 2024) emphasizes the transformation of education through AI (The State Council of the People's Republic of China, 2024). In addition, in 2023, the Ministry of Education of China reinforced

that higher education should embrace comprehensive EE. Specifically, the Ministry highlighted the need to accelerate the digital transformation of higher education and create new models of teaching entrepreneurship in higher education. This includes strengthening the “Innovation and Entrepreneurship Education Platform” (Ministry of Education of China, 2023), which aims to systematically gather and integrate entrepreneurial resources to enhance students’ competencies to seize and create market opportunities by meeting market needs, solving industrial and corporate problems and converting knowledge and skills into new products or services. In the meantime, the Office of the Chief Information Officer (OCIO) of the USA encourages institutions of education at all levels to promote ethical utilization of AI tools, aiming to help the education system achieve intelligent transformation and high-quality development under the guidance of the Executive Order on Promoting American Artificial Intelligence Leadership (U.S. Department of Education, 2025). The European Commission has launched the Digital Education Action Plan (2021–2027), seeking to build a unified European digital education development blueprint; promote premium standards, inclusiveness and accessibility of education; and assist member states in adjusting and optimizing their education systems to better meet the challenges of the digital age (European Commission, 2020). From the teachers’ aspect, to be specific, teachers apply AI pedagogy into class teaching-learning process and course-designing, such as preparing course materials, classroom interaction, tracking attendance, assessing the performance and administering tests (Mudkanna Gavhane and Pagare, 2024). Teachers have basic AI competence in education. Hence, it is evident that it will become a global trend to proactively and rigorously incorporate AI into university education, including EE, which is intended to enhance students’ innovative mindsets and entrepreneurial competencies required for thriving in the AI era.

EE fosters entrepreneurial intention and skills among higher education students to support sustainable growth (Wu *et al.*, 2025). It focuses on imparting basic entrepreneurial literacies and emphasizing stimulating students’ innovative consciousness and entrepreneurship tendencies. Through project-based and experiential learning, entrepreneurial coaching and institutional support or incentives, students are guided to develop adaptability, innovativeness, entrepreneurial spirit and complex problem-solving skills, thereby effectively improving their willingness to take risks, ability to make decisions and insights to identify opportunities in a complex and constantly changing business environment (Dana *et al.*, 2021). AI has been increasingly integrated into EE. And researchers have used it to analyze entrepreneurial psychology with proactive personality and planned behavior theories to enhance personalized learning and improve students’ entrepreneurial competencies and adaptability in dynamic business environments (Zhu and Zhang, 2022). And studies of the impact of AI (e.g. ML, NLP) on EE have also been conducted; for example, Alqahtani (2023) used quantitative experimental methods combined with SEM analysis in a Qatari university to explore the role of AI in improving student entrepreneurship practices and help them cope with an AI-dominated business environment. In addition, the investigation also examined the utilization of generative AI in tertiary educational activities, emphasizing its positive role in optimizing teaching processes and promoting students’ deep learning and skill advancement. By improving students’ AI literacy, critical thinking skills and personalized adaptive learning strategies, the value of generative AI in entrepreneurship is increasingly prominent, providing a new path for cultivating compound talents for the future (Gimpel *et al.*, 2023). Research shows that the deployment of AI with business simulation games (BSGs) in entrepreneurial courses, addressing the limitations of traditional BSGs by enhancing guidance, uncertainty and simulation environments, ultimately improved entrepreneurial attitudes and learning experiences (Chen *et al.*, 2022; Katsanakis,

2025; Velez and Alonso, 2025). Last but not least, several academics have also drawn attention to ethical dilemmas and hold a concerned attitude with the tools being used in the teaching-learning process (Deng *et al.*, 2025; Shahzad *et al.*, 2025; Zheng and Xiao, 2025).

To address these research queries, it is necessary to exploit the framework. First, existing research has largely focused on isolated AI application scenarios (e.g. personalized recommendations and business simulation game integration), failing to systematically explore the mechanisms by which AI influences students' entrepreneurial competencies. Second, few studies have used a unified theoretical framework to analyze the intermediary variables linking "AI application in EE" and "entrepreneurship competencies" (e.g. psychological or cognitive changes in students) with the Stimulus–Organism–Response (SOR) model. Most of the research focuses on the ATM or TPB to explain the entrepreneurial behavior through the mental mechanism (Fayolle and Gailly, 2015; Su and Li, 2021; Su *et al.*, 2021). Third, empirical research uses theoretical models to quantify and validate the relation between EE and students' entrepreneurial competencies in the context of AI. The similarity of the research is extremely scarce in the EE area. Most use the case study or qualitative investigation (Park and Kim, 2025; T. Nuseir *et al.*, 2020; Vecchiarini and Somia, 2023). Therefore, conducting such research is highly necessary to bridge this gap, so as to optimize AI-driven EE, measure AI's impact on entrepreneurial competencies and provide implementable insights to enhance the efficiency of AI-empowered EE in higher education institutions.

Aiming to understand how AI-enabled EE influences students' entrepreneurial competencies, this study integrates a widely recognized theoretical model, which is SOR, as this framework helps to explain how AI adoption in curricula, teaching tools and approaches may influence students' development of entrepreneurial competencies. In this framework, AI-driven EE in higher education serves as the S, students as the O, and their entrepreneurial competencies serves as the R. The study aims to explore: Does AI positively influence EE? How does AI, as an external stimulus (S), influence students' perceived usefulness (PU) and entrepreneurial self-efficacy (ESE) (O), ultimately shaping their entrepreneurial competencies (R) within the SOR model? How can AI-enabled EE be optimized to boost entrepreneurial competencies?

2. Theoretical framework and construction of hypotheses

2.1 Stimulus–Organism–Response model

The SOR framework constructed by Mehrabian and Russell points out that an individual's emotional experience or behavioral response is attributable to external situational stimuli acting on the internal state of the organism, emphasizing the regulatory mechanism of environmental factors on individual psychology and behavior (Mehrabian and Russell, 1974). This internal stimulus processing can be conscious or unconscious, involving the perception and interpretation of environmental factors that affect individual feelings and decisions. The model can successfully explain the behavioral differences caused by the combined effects of stimulus and cognitive factors (Anwar *et al.*, 2023). The SOR model's conceptual flexibility allows it to accommodate diverse stimulus types – both internal and external, manipulated and unmanipulated, experiential and abstract — and to capture a wide range of organismic responses, including perception, emotion, attitude, judgment, belief, and motivation, as well as outcome behaviors such as intention, action and avoidance, among others (Sharma *et al.*, 2021; Wastling *et al.*, 2018).

The SOR model is extensively used in marketing to estimate the formation and drivers of consumer behavior. Numerous studies have consistently pointed out that the interaction mechanism between these three core elements provides a basic framework and theoretical

support for building a theoretical model of consumer behavior (Yoo *et al.*, 1998). Jeong *et al.* (2022) applied it to make the empirical research on the elements of shaping personalized stimuli on consumer responses in a live digital ecosystem. Sohaib *et al.* (2022) applied the model to find that social media marketing activities. The research found that it significantly improved relationship quality factors (e.g., commitment, trust and satisfaction). Thereby, it positively improved the online repurchase intention of consumers in the e-commerce industry. The behavioral response to the stimulus through a mediator mostly refers to the cognitive to affective process of the organism, such as emotion, satisfaction and motivation.

The SOR was also put into revealing the internal mechanisms in higher education research of various fields, with emotions and experience as mediating variables (Goi *et al.*, 2018). For instance, Zhang *et al.* (2021) held that students' learning satisfaction was analyzed as a response to social support and interaction stimuli, mediated by self-efficacy and transferable skills. Yang *et al.* (2021) demonstrated that in e-learning environments, perceived closeness, control and peer influence positively impact students' self-efficacy and well-being, thereby enhancing their learning motivation. Notably, EE significantly shaped undergraduates' entrepreneurial intentions and behaviors, which entrepreneurial alertness and motivation serve as a conduit for these two aspects within the digital context (Alzahrani and Bhunia, 2024), as well as entrepreneurial passion and self-confidence (Cai *et al.*, 2021).

As to those educational studies, the research adopts the model, specifically, AI-driven EE serves as the S, students as the O and their entrepreneurial competencies as the R. In doing so, it explores how AI in EE stimulates individuals' PU and ESE, thus further enhancing their entrepreneurial competencies to deal with complicated situations and future challenges. See Figure 1

2.2 Adoption of AI in higher education and entrepreneurship education

AI is developing rapidly and effectively to solve complex problems and promote business (Kraus *et al.*, 2020; Machucho and Ortiz, 2025), entrepreneurship (Kusetogullari *et al.*, 2025; Short and Short, 2023) and education (Deng *et al.*, 2024; Ouyang *et al.*, 2022). Being considered for helping handle problems for entrepreneurs, AI is creating new entrepreneurial opportunities and renewing entrepreneurial processes (Chalmers *et al.*, 2021; Uriarte *et al.*, 2025). As AI continuously threatens to disrupt and reconstruct higher education, EE is expected to undergo ongoing transformation in response to emerging technological

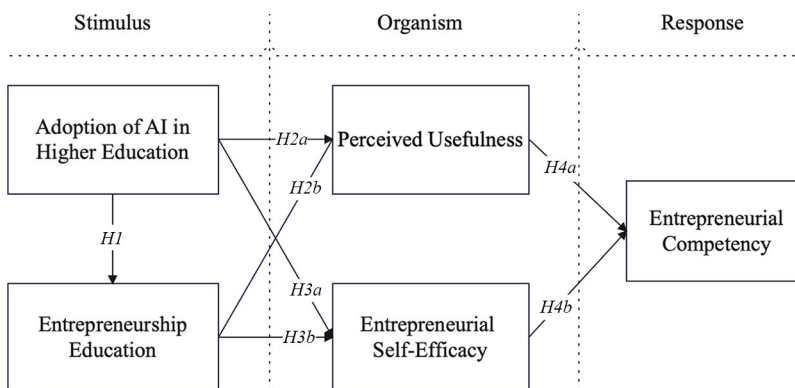


Figure 1. Proposed model

paradigms and shifting digital standards. It makes universities under mounting demands to train graduates with entrepreneurial mindsets to help improve the literacies (e.g. critical thinking, creative thinking), which are the core literacy for an entrepreneur through EE (Essel *et al.*, 2024; Pirhadi *et al.*, 2023), aiming to align with the needs and challenges of the AI-dominated society. Although there is increasing advocacy for integrating AI into curricula, educators have yet to fully use AI in educational settings (Celik, 2023; Gârdan *et al.*, 2025). Meanwhile, the attitude towards AI and entrepreneurship is ambivalent (Jeremiah, 2024; Shepherd and Majchrzak, 2022). Most people are enthusiastic and hold that it enhances student learning, but some are concerned and fear it because of the impediment to cultivating higher-order thinking in learning (Deng *et al.*, 2024; Zheng and Xiao, 2025). As such, this paper makes an academic attempt to analyze how the adoption of AI may affect university EE through empirical data. We begin with the hypothesis:

H1. AAHE will positively contribute to the EE in universities.

2.3 Perceived usefulness

PU refers to individuals having confidence in using a given technology to enhance their performance, which is one of the core elements within the Technology Acceptance Model (TAM). In this context, a system is considered to possess high PU when users perceive a clear and positive linkage between its application and improved task efficiency (Davis, 1989), which offers a coherent theoretical framework for interpreting the key determinants that drive individuals to adopt technological innovations (Putro and Takahashi, 2024). In the educational context, the measurement of PU typically includes aspects such as whether the technology enhances learning efficiency and whether it helps improve learning outcomes or performance (Fathema *et al.*, 2015). Within the business context, AI profoundly shapes entrepreneurial activities by influencing four pivotal areas: opportunity recognition, strategic decision-making, operational efficiency and the advancement of education and academic inquiry. By acquiring specialized training or mastering AI-related tools, entrepreneurs can better address emerging challenges and narrow the gap between entrepreneurial theories and practical applications (Giuggioli and Pellegrini, 2023). Emerging enterprises may strategically adopt AI as an enabler of innovation and improved operational efficiency rather than a mere replacement for labor, thereby facilitating accelerated growth, enhancing decision-making processes and delivering greater value to stakeholders. Hence, the adoption of AI in entrepreneurial practical teaching will improve the efficiency of study, such as shortening the knowledge internalization cycle and enhancing practical relevance, by connecting theoretical knowledge with real business scenarios. Thus, we hypothesize that:

H2a. AAHE will positively contribute to PU.

H2b. EE will positively contribute to PU.

2.4 Entrepreneurial self-efficacy

ESE, in particular, refers to an individual's conscious belief in their ability to successfully perform entrepreneurial tasks (Newman *et al.*, 2019). ESE is a key cognitive construct that bridges environmental influences and entrepreneurial behavior (Carr and Sequeira, 2007). As AI tools, such as ChatGPT, become embedded in routine activities, they progressively function as adaptive cognitive assistants, delivering immediate support for informed decision-making and effective problem resolution (Duong and Nguyen, 2024; Huy *et al.*,

2023). These collaborative interactions help to enhance individuals' confidence and their ability to create and manage digital businesses or apply advanced technological tools in their businesses (Duong and Nguyen, 2024; Upadhyay *et al.*, 2022), thereby fostering entrepreneurial confidence. Besides, EE enhances students' entrepreneurial knowledge and confidence by offering theoretical foundations, practical skills, and experiential learning (Handayati *et al.*, 2020). Therefore, AI-enabled EE could promote university students' knowledge acquisition, boost their self-confidence, and facilitate the development of their entrepreneurial competencies. Thus, we hypothesize that:

H3a. AAHE will positively contribute to ESE.

H3b. EE will positively contribute to ESE.

2.5 Entrepreneurial competencies

Entrepreneurial competencies encompass the knowledge, skills, attitudes and behaviors that facilitate individuals in recognizing and leveraging entrepreneurial opportunities. The distinctiveness of entrepreneurial competencies significantly enhances their influence on organizational performance and strengthens entrepreneurs' capacity to generate sustainable competitive advantages within their ventures (Gunawan, 2024). EE serves as a pivotal mechanism to enhance students' entrepreneurial competencies (Handayati *et al.*, 2020). First, AI through the Machine Learning, Big Data Analytics, Adaptive Learning Systems, Chatbots, AI-driven Simulations and Serious Games, facilitates students with opportunity identification and entrepreneurial learning. This stimulates the PU, improving the entrepreneurial competencies of students, such as opportunity Identification, action planning and implementation, collaboration and risk awareness and mitigation (Chen, 2023). Second, from the perspective of psychology, self-efficacy is a core resilient psychological orientation (Ridwan *et al.*, 2024), enhancing individuals' sense of control, resilience and perseverance in the face of challenges, risks and failures. In addition, self-confidence can motivate individuals to maintain higher motivation, interest, beliefs and expectations, which may lead to higher entrepreneurial ability (Xie and Wang, 2025). Consequently, in the process, students exhibit greater self-efficacy and are more actively involved in entrepreneurial practice and accumulate theoretical literacy and practical ability (Caliendo *et al.*, 2023). Thus, we hypothesize that:

H4a. PU will positively contribute to EC.

H4b. ESE will positively contribute to EC.

2.6 Mediator

In our study, PU and ESE serve as mediators, translating the impacts of the stimulus (AAHE and EE) into behavioral responses (entrepreneurial competencies). First, Alkhawaja *et al.* (2022) held that the use of technologies like VR can affect users' PU of the technology, which can affect their engagement and learning efficiency, among other learning outcomes. In digital learning environments, PU acts as a mediator, linking the technological environment with the outcomes of usage behavior (Wong *et al.*, 2023). Second, previous findings demonstrate that ESE mediates the relationships between predictors – such as entrepreneurial education (Amani *et al.*, 2024) and ChatGPT – and individuals' start-up intentions or subsequent entrepreneurial behavior. This outcome echoes Bandura's (2011) assertion in Social Cognitive Theory that self-efficacy is fundamental to behavioral

performance. In today's AI-influenced entrepreneurial settings, the need to work with emerging technologies and pursue innovative opportunities makes this mechanism even more essential.

H5a. PU functions as an intermediary mechanism through which AAHE and EE influence students' EC.

H5b. ESE functions as an intermediary mechanism through which AAHE and EE influence students' EC.

H6a. AAHE enhances EC through a sequential mediation of EE and PU.

H6b. AAHE enhances EC through a sequential mediation of EE and ESE.

3. Research design

3.1 Measurement instrument

In this research, the measurement instrument was developed twice; all construct items are cited from existing literature with contextual modifications. For the first time, the items of the variable of PU are from [Chatterjee et al. \(2021\)](#); however, these questions more fit the context of manufacturing and production firms than university students for learning with AI. The items of ESE are from [Ahlin et al. \(2014\)](#). For the article, it has 11 items (e.g. I'm able to conduct market analysis) and the problem is that some of the items have a high degree of overlap with EC and are easily grouped together in factor analysis. After collecting questionnaires from 355 students, we found that the questionnaire model did not fit well, so we adjusted the questionnaire to the following: Specifically, the four items measuring AAHE are drawn from [Chatterjee and Bhattacharjee \(2020\)](#). six items of EE are from [Xu et al. \(2023\)](#). Six items of PU are from Davis (1989). 19 items of ESE are from [Karlsson and Moberg \(2013\)](#), which have five dimensions: searching (S), planning (P), marshaling (M), implementing human resources (IHR) and implementing financial resources (IFR). Nine items of EC are from [Seraj et al. \(2022\)](#). Eventually, a five-point Likert scale was developed, with "1" = "strong disagreement" and "5" = "strong agreement."

3.2 Data collection procedure

This study was conducted in three universities in eastern China: one in Zhejiang and two in Shanghai. These universities were selected for their strategic location and economic importance in the Yangtze River Delta – one of China's most developed areas and a leader in the AI industry ([Xu et al., 2022](#)). Prestigious institutions such as Tongji University and other research centers in the region regard AI as a core discipline, investing heavily in talent development and scientific research ([Liang and Hu, 2020](#)). The survey was conducted twice because of the poor quality of the instrument in the first round, leading to the bad model fit indices. The second time, a total of 602 questionnaires were collected through convenience sampling around April and May 2025; finally, 558 valid responses were used. The respondents covered a variety of majors, including business, engineering, social sciences and so on, and were enrolled in entrepreneurship-related courses or participated in university-level innovation and entrepreneurship programs. This sample size meets the general requirement of ten times of questions for SEM.

3.3 Data analysis

In this study, the proposed model was tested by SEM. It is a research method that is widely used in social and behavioral sciences. Although various SEM software packages exist,

many leading tools are commercial or closed source. The R package lavaan was developed within the RStudio environment for latent variable modeling (Rosseel, 2012). The analysis followed three steps:

- (1) assessment of construct reliability using Cronbach's alpha and composite reliability;
- (2) CFA to validate the measurement model; and
- (3) assessment of the structural model for examining the hypothesized associations among latent constructs.

All stages of the analysis were performed using RStudio.

4. Result

4.1 Respondents' demographics

Table 1 presents an outline of the respondents' demographic features. Based on the descriptive statistics, amount of 558 valid responses were used. The sample exhibited a marginal predominance of female participants (53.41%) over male participants (46.59%). For the age group, participants were predominantly in the 17–20 age group (84.95%) and then aged 21–24 (14.16%) and the minority were aged 25–28 (0.90%). For education level, most participants were bachelor's degree candidates (97.49%), with only 1.25% is associate or master's degree candidates. As for grade level, freshmen accounted for the largest proportion (78.32%), followed by sophomores (9.68%), juniors (8.78%), seniors (1.97%) and master's students (1.25%).

4.2 Measurement model

Table 2 illustrates that Cronbach's alpha of AAHE, EE, ESE, PU and EC accounted for 0.943, 0.950, 0.967, 0.982 and 0.965, all above 0.7 (Shrestha, 2021), indicating internal consistency reliability. Standardized loadings were suggested to be higher than the 0.7 threshold (Panahi *et al.*, 2023), whereas CR and AVE of scales were suggested to be over benchmarks of 0.7 and 0.5 (Ab Hamid *et al.*, 2017). In this research, the standardized loading values spanning from 0.831 to 0.945, the CR values spanning from 0.944 to 0.978 and the AVE values spanning from 0.755 to 0.899, representing the item reliability, conceptual

Table 1. Demographic overview

Category	Group	Frequency	%
Gender	Male	260	46.59
	Female	298	53.41
Age group	17–20	474	84.95
	21–24	79	14.16
	25–28	5	0.90
Education	Associate level	7	1.25
	Bachelor's level	544	97.49
	Master's level	7	1.25
Grade	Freshman	437	78.32
	Sophomore	54	9.68
	Junior	49	8.78
	Senior	11	1.97
	Master's student	7	1.25

Table 2. Assessment of the internal convergence of indicators

Construct	Indicator	Standardized loading	Z-value	p-value	M	SD	Cronbach's α	AVE	CR	R ²
AAHE	AAHE1	0.926	121.202	0.000	3.952	0.868	0.943	0.807	0.944	–
AAHE	AAHE2	0.925	120.418	0.000	3.896	0.915				
AAHE	AAHE3	0.836	60.090	0.000	3.862	0.925				
AAHE	AAHE4	0.903	98.474	0.000	3.882	0.909				
EE	EE1	0.868	74.700	0.000	3.699	0.941	0.950	0.761	0.950	0.491
EE	EE2	0.873	77.070	0.000	3.622	0.982				
EE	EE3	0.871	76.164	0.000	3.586	0.986				
EE	EE4	0.831	58.227	0.000	3.742	0.952				
EE	EE5	0.892	89.320	0.000	3.681	0.952				
EE	EE6	0.896	93.111	0.000	3.679	0.951				
ESE_S	ESE1	0.894	89.991	0.000	3.330	1.037	0.967	0.899	0.978	0.449
ESE_S	ESE2	0.904	97.312	0.000	3.371	0.994				
ESE_S	ESE3	0.926	118.962	0.000	3.353	0.982				
ESE_P	ESE4	0.881	83.238	0.000	3.326	0.989				
ESE_P	ESE5	0.903	99.997	0.000	3.401	1.001				
ESE_P	ESE6	0.895	93.505	0.000	3.235	1.038				
ESE_P	ESE7	0.888	88.043	0.000	3.332	1.018				
ESE_M	ESE8	0.886	84.186	0.000	3.351	1.023				
ESE_M	ESE9	0.849	64.747	0.000	3.523	1.000				
ESE_M	ESE10	0.885	83.193	0.000	3.489	1.023				
ESE_IHR	ESE11	0.882	85.914	0.000	3.435	1.011				
ESE_IHR	ESE12	0.869	77.863	0.000	3.392	1.005				
ESE_IHR	ESE13	0.902	102.706	0.000	3.520	0.984				
ESE_IHR	ESE14	0.896	97.219	0.000	3.439	0.984				
ESE_IHR	ESE15	0.875	81.482	0.000	3.554	0.953				
ESE_IHR	ESE16	0.881	85.466	0.000	3.444	0.999				
ESE_IFR	ESE17	0.940	148.292	0.000	3.443	1.002				
ESE_IFR	ESE18	0.945	156.809	0.000	3.387	1.001				
ESE_IFR	ESE19	0.922	121.733	0.000	3.394	1.007				
PU	PU1	0.903	105.276	0.000	3.989	0.893	0.982	0.832	0.967	0.665
PU	PU2	0.911	113.840	0.000	3.903	0.894				
PU	PU3	0.933	146.100	0.000	3.941	0.896				
PU	PU4	0.905	107.112	0.000	3.900	0.905				
PU	PU5	0.907	109.563	0.000	3.989	0.893				
PU	PU6	0.911	113.348	0.000	3.970	0.887				
EC	EC1	0.889	91.851	0.000	3.452	0.983	0.965	0.755	0.965	0.688
EC	EC2	0.892	93.945	0.000	3.477	0.989				
EC	EC3	0.840	63.523	0.000	3.480	0.995				
EC	EC4	0.852	68.695	0.000	3.364	1.014				
EC	EC5	0.842	64.576	0.000	3.315	1.054				
EC	EC6	0.893	94.701	0.000	3.355	1.002				
EC	EC7	0.883	87.285	0.000	3.389	1.012				
EC	EC8	0.869	77.833	0.000	3.493	0.995				
EC	EC9	0.859	72.416	0.000	3.572	0.937				

reliability and convergent validity of the concept, respectively, from which the reliability and convergent validity of each research concept in the sample can be evaluated.

Discriminant validity was assessed with the methods of the Fornell–Larcker (F-L) criterion (Fornell and Larcker, 1981) and the Heterotrait–Monotrait ratios (HTMT) (Henseler *et al.*, 2015) (see Table 3). Bold values indicate the strongest correlation for each subconstruct in each column (Fornell and Larcker, 1981). Although six Fornell–Larcker violations were observed for the second-order construct ESE and its first-order dimensions (ESE_S = 0.908, ESE_P = 0.892, ESE_M = 0.874, ESE_IHR = 0.884 and ESE is 0.948), these violations are expected due to their nested conceptual structure. ESE is a higher-order construct comprising these subdimensions, and high correlations among them do not indicate poor discriminant validity. To some extent, the high correlation shared by the first-order and higher-order constructs is attributed to the modeling approach (Becker *et al.*, 2012). Furthermore, the HTMT values were used to assess the discriminant validity of the SEM

Table 3. Reliability, convergent validity and discriminant validity statistics

Construct	F-I criterion							HTMT criterion						
	ESE_S	ESE_P	ESE_M	ESE_IHR	ESE_IFR	ESE	EC	ESE_S	ESE_P	ESE_M	ESE_IHR	ESE_IFR	ESE	EC
ESE_S	0.908													
ESE_P	0.903	0.892						0.766						
ESE_M	0.916	0.944	0.874					0.719	0.740					
ESE_IHR	0.897	0.925	0.938	0.884				0.699	0.711	0.738				
ESE_IFR	0.844	0.869	0.882	0.864	0.936			0.706	0.714	0.696	0.747			
ESE	0.936	0.965	0.978	0.959	0.901	0.948		0.747	0.753	0.745	0.753	0.752		
AAHE	0.565	0.582	0.59	0.578	0.544	0.603	0.898	0.488	0.438	0.458	0.473	0.493	0.469	
EE	0.589	0.607	0.615	0.603	0.567	0.629	0.701	0.486	0.463	0.467	0.471	0.467	0.470	0.553
PU	0.502	0.517	0.524	0.514	0.483	0.536	0.798	0.439	0.391	0.411	0.437	0.426	0.422	0.654
EC	0.769	0.793	0.804	0.788	0.741	0.822	0.487	0.593	0.616	0.602	0.615	0.618	0.610	0.382
								0.869	0.534	0.639	0.534	0.382	0.484	0.425

model, and the findings in Table 4 are all below the 0.85 threshold. This indicates adequate discriminant validity (Henseler et al., 2015).

4.3 Structural model

Standardized model fit indicators were used to validate the overall model structure (Zhang and Savalei, 2016). The model fit when χ^2/d is < 5 is acceptable. It is recommended that TLI and IFI should be > 0.90 , NFI and CFI should be > 0.9 , REMSEA and SRMR and RMR should be < 0.08 , PNFI should be > 0.5 . See Table 4. This study reports the model fit statistics of the hypothesized model, including the following indicators: $\chi^2/d = 3.261$, RMSEA = 0.064, RMR = 0.032, SRMR = 0.034, CFI = 0.936, TLI = 0.932, NFI = 0.910, IFI = 0.936, PNFI = 0.853. These data illustrate that the model fits well, supporting further hypothesis testing.

The hypothesized associations were analyzed using SEM to validate the theoretical framework. The R^2 values for the endogenous variables – EE (0.491), ESE (0.449), PU (0.665) and EC (0.688) – as shown in Table 3, exceed the benchmark thresholds proposed by Cohen (2013), suggesting strong explanatory power of the proposed model.

Table 5 and Figure 2 present the hypothesis testing outcomes. The findings reveal that AAHE significantly and positively influenced EE ($\beta = 0.701, p < 0.001$), PU ($\beta = 0.631, p < 0.001$) and ESE ($\beta = 0.315, p < 0.001$). Furthermore, EE was positively associated with both PU ($\beta = 0.238, p < 0.001$) and ESE ($\beta = 0.407, p < 0.001$). In addition, PU contributed positively to EC ($\beta = 0.132, p < 0.001$), while ESE demonstrated a strong positive relationship with EC ($\beta = 0.748, p < 0.001$). Collectively, all hypothesized relationships were statistically supported.

Mediation analysis, as shown in Table 6 and Figure 3, revealed that AAHE had a significant indirect impact on college students' EC through PU ($\beta = 0.145, p = 0.007$), indicating that AAHE enhances students' PU of AI tools, thereby strengthening their EC. However, the indirect effect of EE via PU was not significant ($\beta = 0.039, p = 0.085$), suggesting that PU is not the primary mechanism by which EE influences EC. In contrast, ESE exhibited a strong and stable mediating role in both pathways: the indirect effects of AAHE and EE on EC were $\beta = 0.408 (p < 0.001)$ and $\beta = 0.407 (p < 0.001)$, respectively, representing the strongest effect among all pathways. Furthermore, regarding chain mediation, the path AAHE $\rightarrow$ EE $\rightarrow$ PU $\rightarrow$ EC was non-significant, while the chain mediation effect of AAHE $\rightarrow$ EE $\rightarrow$ ESE $\rightarrow$ EC was significant ($\beta = 0.400, p = 0.002$), indicating that AAHE can further enhance students' ESE by improving the quality of EE,

Table 4. Model fit evaluation

Fit index	Value	Model fit evaluation
χ^2	2892.622	Sensitive to sample size
df	887.000	–
χ^2/df	3.261	Acceptable
RMSEA	0.064	Acceptable
RMR	0.032	Good
SRMR	0.034	Good
CFI	0.936	Good
TLI	0.932	Good
NFI	0.910	Good
IFI	0.936	Good
PNFI	0.853	Acceptable

Table 5. Hypotheses testing results

Hypotheses	Path	Estimate	Std. error	z-value	p-value	Std. estimate	Supported [yes/no]
<i>H1</i>	EE → AAHE	0.713	0.039	18.217	0.000	0.701	Yes
AAHE + EE → PU							
<i>H2a</i>	AAHE → PU	0.634	0.043	14.717	0.000	0.631	Yes
<i>H2b</i>	EE → PU	0.234	0.040	5.860	0.000	0.238	Yes
AAHE + EE → ESE							
<i>H3a</i>	AAHE → ESE	0.339	0.054	6.335	0.000	0.315	Yes
<i>H3b</i>	EE → ESE	0.431	0.054	7.997	0.000	0.407	Yes
PU + ESE → EC							
<i>H4a</i>	PU → EC	0.142	0.034	4.225	0.000	0.132	Yes
<i>H4b</i>	ESE → EC	0.755	0.041	18.587	0.000	0.748	Yes

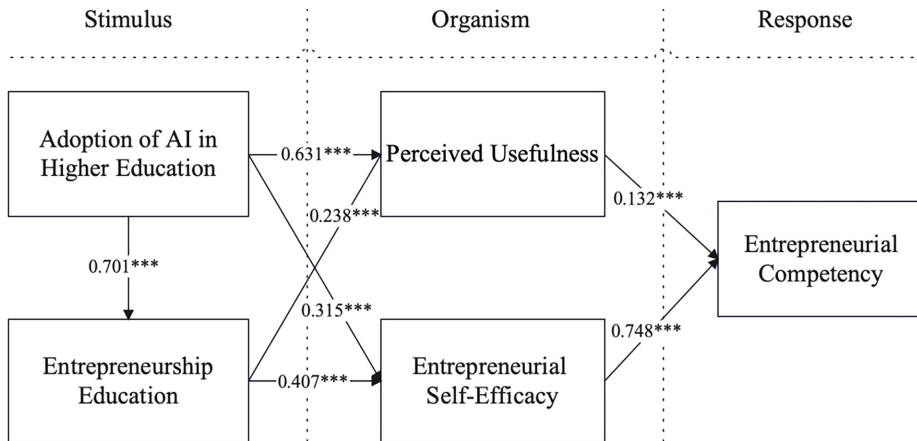


Figure 2. Hypotheses testing results

Table 6. Mediator effect

Mediation coefficient paths	Indirect effects	SD	t-value	p-value	LL	UL
AAHE → PU → EC	0.145	0.054	2.678	0.007	0.028	0.245
EE → PU → EC	0.039	0.023	1.722	0.085	0.005	0.091
AAHE → ESE → EC	0.408	0.110	3.702	0.000	0.191	0.632
EE → ESE → EC	0.407	0.115	3.547	0.000	0.232	0.680
AAHE → EE → PU → EC	0.038	0.022	1.764	0.078	0.005	0.090
AAHE → EE → ESE → EC	0.400	0.131	3.044	0.002	0.209	0.724

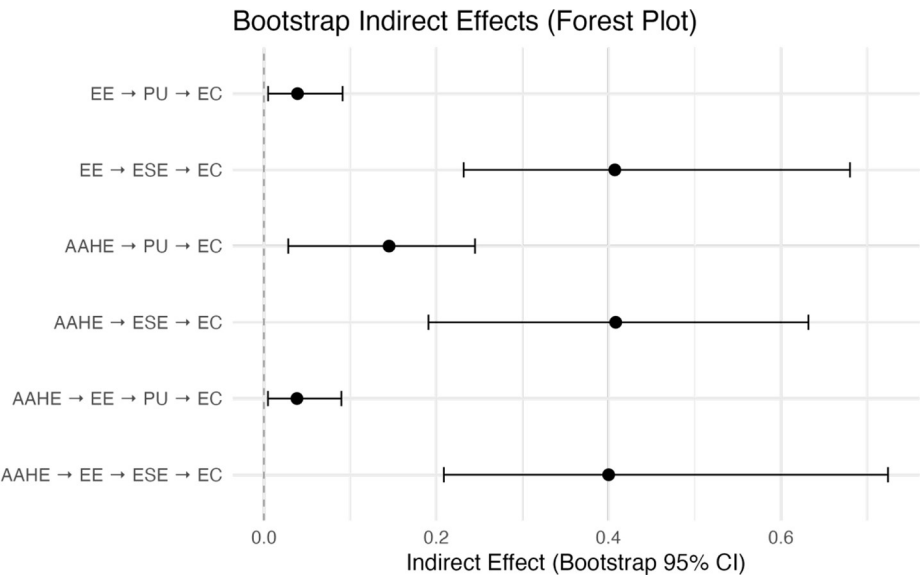


Figure 3. Bootstrap indirect effects

ultimately promoting their EC. Overall, ESE is the most critical and stable psychological mediator variable in cultivating students’ EC.

5. Discussion

Based on the theory of SOR, this research builds a model to show how the application of AI in EE in universities helped students improve their entrepreneurial competencies, with PU and ESE as the organism perception.

Primarily, from the research, we can see that to cultivate students’ entrepreneurial competencies, adopting AI in higher education helps boost the efficiency and effectiveness of EE greatly ($\beta=0.701$, $p<0.001$). With the continuous advancement of AI, its incorporation into course design has obviously improved classroom interactivity, personalization and engagement, leading to the transformation of entrepreneurship classroom style to student-centeredness and the model of instruction becomes multi-interactive and inquiry-based. AI-driven learning and teaching styles, such as the integration of prompt engineering skills, virtual entrepreneurship simulations and data-driven market analysis, all offer students a more immersive learning experience, which serves to encourage and reinforce students’ active and critical thinking, collaboration, innovation and creativity (Lee and Palmer, 2025; Ruiz-Rojas *et al.*, 2024; Weng *et al.*, 2025). This is because students can be highly participative as AI gives real-time feedback. And as such, students can more easily grasp entrepreneurial knowledge, identify business opportunities and complete the processes from generating creative ideas to conducting market research and commercial implementation with AI assistance. In EE, the use of AI for an instructor not only boosts students’ entrepreneurial intention but also provides practical technical support from the university for implementing entrepreneurial ideas (Xie and Wang, 2025). For example, AI-driven applications like ChatGPT may significantly transform and improve multiple dimensions of the entrepreneurial processes. These include facilitating idea generation,

supporting the development of business models, assisting in business plan formulation and enabling more efficient execution of customer interviews. Thus, it shortens the time, improves the work efficiency and enhances the effectiveness of EE (Vecchiarini and Somia, 2023). The adoption of AI in higher education is not just about adapting a technological tool in the EE but also a catalytic enzyme for transforming EE from teaching to doing. Through redefining EE between teacher and student relationships, and the methods for knowledge acquisition, AI creates a more contextualized, efficient and intelligent learning environment for understanding entrepreneurship processes and mastering entrepreneurship skills, thereby laying the foundation for the students' entrepreneurial competencies (Ragolane et al., 2025).

Furthermore, the results show that both AAHE and EE significantly affect PU and ESE (H2a–H3b), indicating that AI education and EE can provide students with important cognitive resources at both the cognitive and competency levels. For PU, the adoption of AI in higher education has a significant effect on students' cognition ($\beta = 0.631$, $p < 0.001$). When students engage with AI-assisted learning, they perceive the practical value of AI tools in acquiring entrepreneurial information and knowledge, designing entrepreneurial projects, integrating entrepreneurial resources and simulating entrepreneurial activities, which combine to strengthen their perception of the usefulness of AI under the real experience, persuasively and enduringly (Ali et al., 2025). By comparison, traditional EE has less of an effect on PU ($\beta = 0.238$, $p < 0.001$), possibly because the curricula are focused more on business knowledge and skills rather than engaging with technological tools, making it difficult to foster students' strong recognition of AI applications. For the ESE, both the adoption of AI in higher education ($\beta = 0.407$, $p < 0.001$) and EE ($\beta = 0.315$, $p < 0.001$) demonstrate a moderate positive effect. Obviously, the application of AI technologies and tools in implementing entrepreneurial activities reduces risk, increases repeatability and enables faster feedback, providing a safer simulation chance to experiment with entrepreneurial tasks. Thus, it enhances their ESE (Chen et al., 2022). Meanwhile, systematic entrepreneurship courses through systematic teaching, case studies and practical projects, offer students a clear objective of entrepreneurial knowledge and assurance of believing in entrepreneurial success. Together, these two dimensions constitute a complementary mechanism that facilitates the enhancement of learners' self-efficacy. In summary, the convergence of AI and tertiary education – particularly in the domain of entrepreneurship instruction – not only improves students' technological skills but also strengthens their cognitive and psychological experiences, maximizing the AI's value in entrepreneurship.

Meanwhile, EC was significantly positively predicted by PU ($\beta = 0.132$, $p < 0.001$) and ESE ($\beta = 0.748$, $p < 0.001$) (H3a–H3b), especially ESE, which had the strongest influence, suggesting that the formation of entrepreneurial ability depends more on students' belief system and ability judgment. ESE reflects students' confidence in grasping and achieving entrepreneurial skills, such as marketing insight, opportunity identification and team building. High ESE drives students' confidence into action with the use of AI, motivating them to continuously engage in entrepreneurial explorations and practices as starting up companies, sharpening their business acumen. And as a result, students can accumulate entrepreneurial experiences and enhance their ability to overcome entrepreneurial challenges. Ultimately, the adoption of AI in EE facilitates the evolution of business ideas to launching a business, contributing to fostering entrepreneurial capability. This observation aligns with Bandura's theory of self-confidence, suggesting that individuals with elevated self-assurance tend to convert entrepreneurial intentions more effectively into tangible outcomes. In essence, heightened self-confidence correlates positively with enhanced entrepreneurial performance (Bandura, 1982). In contrast, while PU also presents a beneficial effect on EC, its mechanism path is more indirect, although it is also one of the prerequisites for enhancing entrepreneurial

competencies. According to the theory of TAM, the endeavors occur only when students generate an actual usage need and entrepreneurial intentions. It is based on the perception that integrating AI into their entrepreneurial actions can substantially enhance their entrepreneurial competencies. Therefore, the influence of PU depends on students' adoption and continuous use in entrepreneurial behavior. In fact, students from the examples may have a sense of entrepreneurship after the EE, but rarely take action into entrepreneurship. Aligning with the TAM, its promoting effect will be limited (Davis, 1985).

Regarding the mediating effects, first, the mediating role of PU is relatively limited. While the path AAHE $\rightarrow$ PU $\rightarrow$ EC is significant, the indirect effect of EE $\rightarrow$ PU $\rightarrow$ EC is not significant and the chain mediation of AAHE $\rightarrow$ EE $\rightarrow$ PU $\rightarrow$ EC also did not reach a significant level. This indicates that while students' PU of AI helps improve entrepreneurial competencies, this effect is unstable and not the main mechanism by which EE influences entrepreneurial competencies. In contrast, ESE is the strongest and most stable mediating variable. Both AAHE and EE significantly affect EC through ESE ($\beta = 0.408$ and $\beta = 0.407$, respectively), indicating that ESE is the core psychological path connecting AI education, EE and entrepreneurial competencies. Furthermore, the chain mediation AAHE $\rightarrow$ EE $\rightarrow$ ESE $\rightarrow$ EC is also significant, suggesting that AI-empowered education not only directly improves students' self-efficacy but also further enhances their self-efficacy by improving the quality of EE, thereby continuously promoting the development of entrepreneurial competencies. Overall, in the context of AI's deep integration into education, ESE is a key mechanism for promoting entrepreneurial competencies, while PU plays a relatively secondary role. In other words, simply making students aware of the "usefulness" of AI is insufficient to enhance their abilities; the key lies in the synergy between AAHE and EE, enabling students to build confidence, master skills and develop robust self-efficacy in real-world learning and application scenarios. This finding also suggests to universities that the value of AI empowerment ultimately depends on how it supports students' self-efficacy and ability building, rather than the technology itself. AI helps enhance these capabilities, but it cannot replace them. AI plays an instrumental role, but it is not the main driving force. Its value lies in "enhancing people," not "replacing people."

6. Conclusions

6.1 Theoretical contributions

Based on the SOR theory, the empirical research makes two theoretical contributions to the adoption of AI in EE. To begin with, the study illustrates the applicability of AI being applied to EE within the SOR theory. With AI and EE being the external environmental stimuli for students, it enhances the students' technological perceptions, recognition and ESE, so as to influence students' entrepreneurial attitudes and behaviors and ultimately cultivate their entrepreneurial competencies. The study also reveals the horizontal progression from "stimulus reception" to "organism change" and finally to "response," which supports the theory in the study of entrepreneurial competencies and extends the boundaries of the SOR theory within the complex field of EE.

Second, the study further reveals that students' cognitive development of entrepreneurship is influenced by the adoption of AI in EE. Specifically, PU and ESE, as the organism variables within the SOR framework, function as the mediating bridges from external stimuli to capability output in the AI-enabled EE. When AI is introduced as an instructional-assistant tool in entrepreneurial courses and other entrepreneurial practices, students gradually create a positive cognitive evaluation because of real interaction and practical application, leading to an increased recognition and reliance on the value of AI, thereby forming a raised sense of PU. Simultaneously, the cognitive transformation from

recognition of AI to evaluating one's own capability gradually enhances students' sense of control and confidence in problem-solving, ultimately fostering their ESE (Jia and Tu, 2024). PU answers the technical cognitive question of "Is AI useful?", while self-efficacy answers the psychological belief of "Can I do this?" These two constructs uncover the internal mechanism by which AI-enhanced EE facilitates EC development.

6.2 Practical contributions

First, the study contributes to the reform and transformation of current modes of EE empirically by adopting AI technologies and tools, reshaping and redefining EE in an AI-dominated world, so as to cultivate the competencies in EE. To be specific, when AI meets education, it not only changes the teaching methods but also helps to develop a profound transformation in cultivation models (Strielkowski *et al.*, 2025). So, policymakers, university administrators, faculty and students should embrace AI and rigorously promote and implement the applications of AI technologies and tools in cultivating talents of innovative and entrepreneurial mindsets, aptitudes and capabilities. As higher education institutions, they should redesign and reconstruct disciplines and instructional models to establish an AI-supported entrepreneurial ecosystem to create an environment oriented toward AI-empowered teaching and learning in EE. Specifically, AI-enabled entrepreneurship incubators (Thottoli *et al.*, 2025), virtual entrepreneurship simulation platforms and AI-guided laboratory assistants are encouraged to be built, AI assistants are adopted to help students with enhanced experiential learning, accumulated practical experience, reduced trial-and-error costs and improved entrepreneurial cognitive competencies (Mu and Zhao, 2024). Meanwhile, universities can hearten to explore innovative "Human-AI Collaboration" models to encourage students to interact with AI in the classroom and change the traditional teaching mode that mainly focuses on root-learning of concepts, definitions and theoretical knowledge. By combining teachers, students and AI to build a three-party participative teaching model, teachers can effectively apply AI for problem construction, prompting design, data analysis and other teaching methods, which helps to make full use of AI technologies and tools in EE. With the AI-enabled entrepreneurial classroom, students are facilitated to identify market opportunities, gain insights into consumer trends and initiate innovative business models, so as to enhance their entrepreneurial competencies in a comprehensive way (Chen *et al.*, 2024).

Second, by integrating AI into EE, this research highlights its critical influence on fostering students' self-efficacy in entrepreneurial competencies and advancing their broader entrepreneurial skill sets. Students' self-efficacy is prominent for students in the symbiotic context of human-AI interactions (Wu *et al.*, 2025). How to enhance students' self-efficacy to cultivate entrepreneurial competencies? The AI capabilities embedded within universities represent a comprehensive synthesis of functional resources – such as digital infrastructure, technological assets, data systems, human capital encompassing both technical and managerial expertise and applied AI competencies, which draw upon established institutional mechanisms like interdepartmental collaboration (Jia and Tu, 2024). This provides students with a stable, intelligent and efficient AI-enabled educational ecosystem. Through the school's AI learning ecosystem, students receive entrepreneurial education while experiencing the conveniences of AI technologies, such as interaction, simulation and cost reduction. This stimulates their interest in learning and their motivation to explore. Through AI-enabled courses and practical exercises, students first develop a systematic entrepreneurial conviction. They then transfer and apply these convictions to real or simulated entrepreneurial situations, gradually strengthening their sense of self-efficacy. This enhanced effectiveness boosts students' psychological resilience and willingness when they face entrepreneurial risks and uncertainties (Duong and Nguyen, 2024), and further enables students to better identify market opportunities, innovate business models,

solve complex problems and demonstrate greater initiative in teamwork. Ultimately, entrepreneurial intentions are successfully transformed into entrepreneurial behavior, supporting the comprehensive development of students' entrepreneurial skills and sustainable competitiveness in the AI era.

Furthermore, the present study also reminds readers of a practical concern that when students lack sufficient understanding of how AI works or do not perceive its helpfulness, they may experience technological stress, cognitive overload or even lower their confidence in their abilities. This psychological burden – commonly referred to as technostress – seriously prevents learning and to be worse, may hinder their ability to internalize entrepreneurial skills. Some universities have begun addressing this. For example, MIT's computer science curriculum is structured to deliver fundamental theoretical and practical knowledge to students, while also catering to their growing interest in interdisciplinary applications, particularly in machine learning and its integration into diverse domains ([MIT News Office, 2018](#)). Similarly, Tsinghua University has demonstrated its strategic commitment to AI education by establishing the Artificial Intelligence Education Center within its Department of Computer Science and Technology ([Tsinghua University Artificial Intelligence General Education Research Center, 2025](#)). However, mixing AI into EE still faces problems. Technology moves fast, but teachers and courses cannot keep up oftentimes. Also, some teachers might not be ready to teach both AI and business topics. To tackle these issues, universities can take a few practical steps. First, they should understand their students – such as their fields of study, backgrounds, current AI knowledge and specific learning needs. This helps in designing layered, flexible curricula that serve students at different levels. Second, schools can form interdisciplinary teaching teams of teachers committed to the integration of AI into curricula. These teams can organize faculty workshops, expert lectures and hands-on training to help instructors stay current. In addition, colleges could explore blended models, such as integrating AI tools into entrepreneurship-focused minors. This kind of pilot program, supported by faculty from multiple disciplines, allows students to work across fields and learn in teams.

6.3 Constraints and suggestions for future research

Though its contributions to understanding AI-enabled EE in terms of PU of AI tools, ESE and entrepreneurial competencies, the limitations of this study are below. First, the sample was exclusively drawn from three universities in the Yangtze River Delta, which is the area of active entrepreneurship and AI technology, but excluding higher education institutions in central, western and northeastern China, where AI infrastructure and EE resources are not as abundant. This geographic bias means the results may not generalize to contexts with limited AI access and other necessary entrepreneurial resources. In addition, the sample structure was unbalanced, with freshmen accounting for 78.32% and undergraduates 97.49%, respectively, while seniors and postgraduates were underrepresented. Because freshmen typically have only preliminary exposure to entrepreneurship courses and limited hands-on experience with AI tools, their responses may underestimate the actual impact of AI on EC development, thus undermining the efficacy of the research.

To address the above-mentioned constraints and extend the current research, several avenues for future studies are proposed. First, strengthening cooperation between universities from diverse geographic regions, it helps to explore how regional differences in AI development moderate the impact of AI-enabled EE. In addition, adopting a quasi-experimental design with an experimental group, namely, AI-integrated EE and a control group of traditional EE, will allow researchers to quantify AI's net effect on entrepreneurial competencies, strengthening causal claims. Second, incorporating moderating variables such as “student AI literacy” and “teacher AI teaching competence” may expose under what

conditions AI-enabled EE is most effective, for instance, whether students with higher AI literacy derive greater benefits from AI tools or whether teacher training in AI integration amplifies the model's effects. In addition, there is a need for extended longitudinal studies to examine the sustained effects of AI EE, for example, examining whether AI exposure during university correlates with subsequent entrepreneurial behaviors, e.g. startup creation, venture performance, so as to provide more practical evidence for the value of AI in cultivating university students' long-term entrepreneurial competencies and self-efficacy.

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Corresponding author

Yanxiang Chen can be contacted at: 601273@zjsru.edu.cn