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Effects of higher education institutes' artificial intelligence capability on students' self-efficacy, creativity and learning performance

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Abstract
Artificial Intelligence (AI) has become an important technology affecting the development of society and education, and it is crucial to explore AI to enhance students' creativity and learning performance. This research proposes the model and hypothesis based on the resource-based theory and related research. AI of higher education institute (HEI) affects students' learning performance and combines the existing literature to develop measurement tools and to obtain a formal questionnaire after pre-research and received 561 valid questionnaires collected from HEIs in China that have applied AI. Then we used SmartPLS 3.0 to construct a partial least squares structural equation model (PLS-SEM) for data analysis on the received data samples. The research results show that: 1) HEIs' artificial intelligence capability is a three-order variable and formed by three formative second-order variables such as resources (data, technical, basic resources), skills (technical skills, teaching applications, collaboration competencies), and consciousness (reform, innovation consciousness); 2) HEIs' artificial intelligence capability significantly affects students' self-efficacy and creativity; 3) HEIs' artificial intelligence capability affects students' learning performance via two mediating variables: student creativity and self-efficacy. This study focuses on AI applications within the HEI, confirms the new explanatory power of resource-based theory in technological practices, and deconstructs the intrinsic mechanics, especially in relationships between students' creativity, self-efficacy, and learning performance. This research also puts forward suggestions to reserve and deploy artificial intelligence resources, improve the digital literacy of teachers and students, use AI to drive teaching and learning, and improve students' creativity and learning performance.

Keywords Artificial intelligence capability · Higher education institute · Learning performance · Student creativity · Self-efficacy · PLS-SEM · Higher-order Constructs

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1 Introduction

Artificial intelligence (AI) is a strategic technology leading a new era of technological, industrial, and social revolution and is having a significant and far-reaching impact on the transformation of education, economic development, social progress, and the international political and economic situation (UNESCO, 2021). AI promotes equitable and adequate quality advancement in education, and the benefit of these technologies for teaching and learning has been discussed in the spotlight nowadays (Bernard et al., 2017; El-Bishouty et al., 2019; Tan, 2020). AI has brought a considerable transformation to the development of teaching and learning (Guilherme, 2019).

AI in education brings predictable and long-term advantages. However, the existing research worldwide focuses on no more than its trends (Huang et al., 2021; Paek & Kim, 2021), concepts (Lee & Lee, 2021), application scenarios (Feng & Law, 2021), integration (Kong et al., 2021), evaluation (Li & Su, 2020), Higher education institute (HEI) (Shan et al., 2021; Wenge, 2021), personalized learning (Liu et al., 2020; Normadhi et al., 2019), and artificial intelligence technologies (Wang & Zhan, 2021; Xu, 2021). We encourage more researchers to facilitate AI systems' capacity (UNESCO, 2021). Huang (2021) believes that artificial intelligence in education enhances students' knowledge, collaboration, and learning abilities. Osetskyi et al. (2020) studied artificial intelligence in education across many countries and found that such modern technology significantly affects the quality of teaching and individual competitiveness. It can also help teachers track students' learning and offer feedback. New technologies, including AI, are often hatched in HEIs, and meanwhile, new technology has nurtured HEI innovation and reform (Wang & Zhan, 2021). Classes involving artificial intelligence technology can stimulate students' interest in learning rather than traditional schooling (Xu, 2021) and achieve better academic results (Shan et al., 2021). Lee and Lee (2021) discussed AI-related concepts, machine learning, natural language processing, and shared real-class cases in self-learning, evaluation, and interaction. Through comparative experiments, Li and Wang (2021) found that AI can help college students be more enthusiastic and diligent in offline lessons. An increasing number of scholars focus on the application of artificial intelligence in education, and it has become an indispensable technical tool with its enormous potential supporting learners and educators nowadays and in the future (Paek & Kim, 2021).

By reviewing the research above on AI in education, currently, the existing literature has not discussed the role of AIC in the HEI on student learning performance (research gap1), and little research under resource-based theory on artificial intelligence capability (AIC) in the HEI (research gap2); and no studies have explored the connection among AIC in the HEI and student creativity, self-efficacy, and learning performance (research gap3). Unlike earlier research, this research will focus on deconstructing the components of AIC at the HEI level and the impact on students' creativity and learning performance, exploring practical countermeasures and solutions and providing research references for the HEIs to use innovative technologies for educational support.

According to the above research limitations, this study conducted a literature review and proposed research hypotheses in Chapter 2. Chapter 3 describes the process of developing measurement tools and receipt collection. Chapter 4 presents the results of the data analysis. In Chapter 5, we have the discussion. Chapter 6 is the conclusion. This research summarizes the connotation and constituent elements of HEIs' AIC by collecting and analyzing the relevant research results, combined with a questionnaire survey and empirical analysis. We analyze the components of AIC in HEIs: resources (data resources, technical resources, basic resources), skills (technical skills, teaching applications, collaboration competencies), and consciousness (reform consciousness, innovation consciousness), a total of three categories and eight subdivision dimensions. It is proven that AIC positively affects students' creativity, self-efficacy, and learning performance. Based on the above conclusions, this study also explores theoretical and practical implications for developing HEIs' AIC to enhance students' creativity, self-efficacy, and learning performance.

2 Literature review and hypothesis

2.1 Literature review

2.1.1 Resource-based theory

Resource-Based Theory (RBT) refers to the differences in performance across organizations due to the resources and capability diversity (Mandal, 2019); furthermore, various technological innovations cause differences between tangible and intangible resources (Barney et al., 2021). Many scholars have used RBT to study the performance relating to resource advantages (Barney et al., 2021; Priem & Butler, 2001). Organizational intangible resources (Barney et al., 2001), tangible resources (Raphael & Schoemaker, 1993), and dynamic capabilities (Teece, 2016) are essential parts to form organizational capabilities (Wilden et al., 2016).

Omondi-Ochieng (2019) conducted a predictive study on the competitiveness of college football teams about RBT and ensured three independent variables of material resources are human resources and organizational resources impact the competitiveness of college football teams. Ma and Dou (2020) combined resource-based theory and the scenario of HEI academic entrepreneurship and investigated the influence of HEI and environmental dimensions on the performance of HEI academic entrepreneurship. Mikalef and Gupta (2021) suggested a definition of artificial intelligence capability (AIC) in the enterprise environment regarding resource-based theory, and they classified AIC into tangible, human, and intangible resources.

2.1.2 Artificial intelligence capability

Due to AI's interdisciplinary and multidimensional nature, the current descriptions has not yet gained consensus (Lee & Lee, 2021). Table 1 shows the descriptions of AI and AIC in the literature.

Kaplan and Haenlein (2019) demonstrate that organizations need to maintain confidence, change, and manage internal and external perspectives to grasp the changes and opportunities brought by AI. New technology practices in HEIs should consider technology configuration (Paek & Kim, 2021), collaborative relationships (Li & Wang, 2021), reform, and innovation (Paek & Kim, 2021), stockpiling digital resources (Lee & Lee, 2021; Mandal, 2019), technology resources (Ransbotham et al., 2017), awareness of reform and innovation (Shan et al., 2021; Wang & Zhan, 2021), enhancement of digital competence and information literacy (Wenge, 2021), and technological competence (Holmstrom, 2021) to accumulate benefits of technical practices (Wang et al., 2021a). In addition, AI technology development in HEIs should concentrate on resources and students' information literacy, data literacy, and technical competence (Huang, 2021). Mikalef and Gupta (2021) classify the components of AIC in enterprises as tangible resources (data, technology, basic resources), intangible resources (technical skills, business skills), and human resources (cross-departmental coordination capabilities, organizational change capabilities, risk propensity). Based on the framework of enterprise AIC presented by Mikalef and Gupta (2021) and the analysis of previous research results, this study defines the AIC of HEI as the capacity to integrate and apply AI technologies (products). We categorize AIC into resources (data resources, technical resources, basic resources), skills (technical skills, teaching applications, collaboration competencies), and consciousness (reform consciousness, innovation consciousness) with eight dimensions (in Fig. 1).

Table 1 The demographic characteristics of the survey

Definition	Literature
Artificial intelligence capability refers to an organization's ability to build, integrate and utilize AI-based resources	Mikalef and Gupta (2021)
An interdisciplinary and comprehensive subject that provides an essential impetus for change in education	Lee and Lee (2021)
A disruptive technology for precision teaching and personalized learning	Wang and Zhan (2021)
A system learns from external data and uses the results to achieve specific goals and tasks	Kaplan and Haenlein (2019)
Intelligent science and technology are based on brain cognition, machine perception and pattern recognition, natural language processing and understanding, and knowledge engineering	Li and Wang (2021)
Adopt intelligent behaviors and sense the environment of the computing agent to act and maximize the chances of success	Poole and Mackworth (2010)
A science and engineering for building intelligent machines	McCarthy (2007)

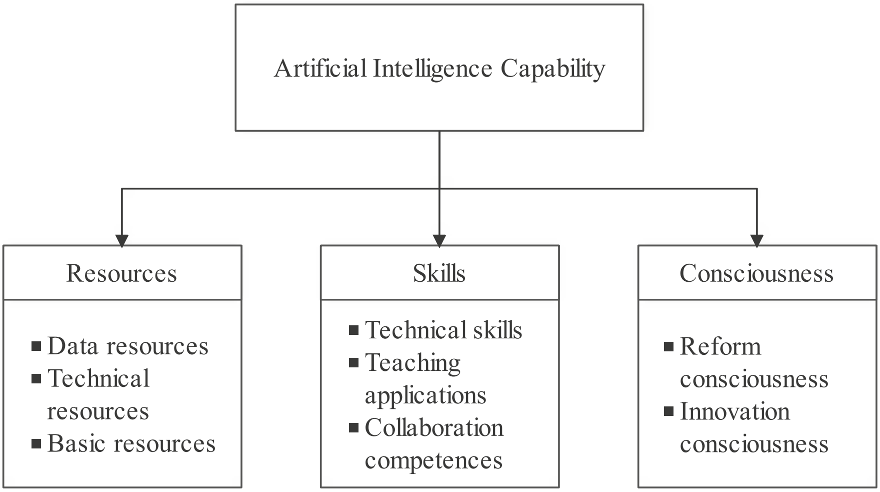

Fig. 1 Framework and components of AIC in HEIs

2.2 Hypotheses and conceptual model

2.2.1 Hypothesis

AI is a systematic device that recognizes, interprets, suspects, and learns from data to achieve organizational and social goals (Mikalef & Gupta, 2021). Information literacy represented by AI facilitates learning activities to perform well (Hu et al., 2020). It provides a way to develop students' creativity, innovation (Zhang & Gao, 2020), and the ability to use technology (Bian & Dong, 2020). It is a technological approach to maximize students' innovation and creativity in the face of social change (Oktradiksa et al., 2021). Learner-tailored learning focuses on student creativity (Colchester et al., 2017) and helps students improve their understanding and problem-solving skills (Zhao et al., 2020). Lin et al. (2013) found that personalized learning systems related to data resource mining can enhance students' creativity. AI benefits by promoting users' creativity (Boden, 1998). According to Memmert and Perl (2009), artificial neural network methods simulate and analyze creative behavior to encourage creativity. The developing AI technologies have entirely improved teaching and learning environments and support innovative thinking practices (Al Hashimi et al., 2019). David (2015) discusses whether AI could help users acquire problem-solving skills and creativity. Muldner and Burleson (2015) operated machine learning and collected data from sensors to assist students in building their creativity classifiers. The importance of AI growing flexibility and creativity in students has been acknowledged widely (Popenici & Ker, 2017). With the boost of the digital revolution, students improve their creativity, technology applications, and other comprehensive skills supported by AI (Crittenden et al., 2019). Artificial intelligence pedagogy positively affects the development of students' information literacy (Loftus & Madden, 2020), thereby enhancing students' self-efficacy. Shneiderman (2020) emphasized that the human-centered concept of AI systems could promote human self-efficacy and creativity. Flink and Cooper-Larsen (2020) argued that AI could improve students' self-efficacy via virtual classes and learning performance (Li & Wang, 2021). Based on the above arguments, the hypotheses proposed in this study are as follows:

Hypothesis 1 (H1): AIC positively affects students' creativity.
Hypothesis 2 (H2): AIC positively affects students' self-efficacy.

Artificial intelligence technologies bring many new paradigms to teaching and learning and students' self-efficacy. Computer proficiency in such teaching environments can achieve the ultimate academic results (Paek & Kim, 2021). User-based adaptive AI can enhance student learning performance (Kim et al., 2013). AI-assisted instructional systems help teachers understand students' academic performance and analyze collected data on learners' behaviors and habits (Ciolacu et al., 2018). Self-efficacy plays a vital role in developing computer and information literacy (Paul et al., 2017). Celik and Yesilyurt (2013) identified that attitudes towards new technologies, computer self-efficacy, and anxiety are significant predictors of computer-based instruction. Those with high efficacy levels tend to achieve better learning performance (Alghamdi et al., 2020). Self-efficacy is the ability to master technology (McCoy, 2010), and mastery of technology applications such as AI positively helps accumulate study improvements (Koć-Januchta et al., 2020). In an empirical study, Chen (2017) found that self-efficacy by computing skills had a positive and significant effect on academic performance. Wei and Chou (2020) indicated that students' computing or Internet self-efficacy significantly impacted online discussion efficiency and course satisfaction. Highly innovative students are more likely to address challenges within environments that use AI, including computers (Wu & Wu, 2020), and these students also tend to reach higher goals than expected. When higher self-efficacy levels are assumed, it will indirectly enrich students' study outcomes (Paek & Kim, 2021). Based on the above arguments, the hypotheses proposed in this study are as follows:

Hypothesis 3 (H3): Students' creativity positively affects learning performance.
Hypothesis 4 (H4): Students' self-efficacy positively affects learning performance.
Hypothesis 5 (H5): AIC positively affects students' learning performance.

2.2.2 Conceptual model

Higher-order variables (model) are deformed from lower-order variables (model), while lower-order variables can be reflective or formative (Hair et al., 2022). Furthermore, second-order variables can be formed from first-order variables, and third-order variables can be formed from second-order variables (Hair et al., 2022). Construction of the above variable types (Formative or Reflective) and structures based on previous literature (Lee & Cadogan, 2013; Tehseen et al., 2017; Mikalef & Gupta, 2021), this study defines AIC as third-order variables, with resources, skills, and consciousness defined as second-order variables (Table 2).

This study focuses on the research question of the impact of AIC on students' creativity and learning performance in HEIs. Based on the analysis of relevant literature on AIC, creativity, learning performance, and self-efficacy, a third-order variable model and a dual-mediated integration model of AIC constructed is shown in Fig. 2 (Lee & Lee, 2021; Li & Wang, 2021; Paek & Kim, 2021; Ransbotham et al., 2017; Shan et al., 2021; Wenge, 2021). The research model will explore whether AIC as a third-order variable can be composed of three formative second-order constructs (Mikalef & Gupta, 2021) while exploring the relationship with students' creativity, self-efficacy, and learning performance.

Table 2 Latent constructs and sub-dimensions

Third-order	Type	Second-order	Type	First-order	Type
Artificial intelligence capability	Formative	Resources	Formative	Data resources	Formative
				Technical resources	Formative
				Basic Resources	Formative
		Skills	Formative	Technical skills	Reflective
				Teaching application	Reflective
				Collaborative competence	Reflective
		Consciousness	Formative	Reform consciousness	Reflective
				Innovation consciousness	Reflective

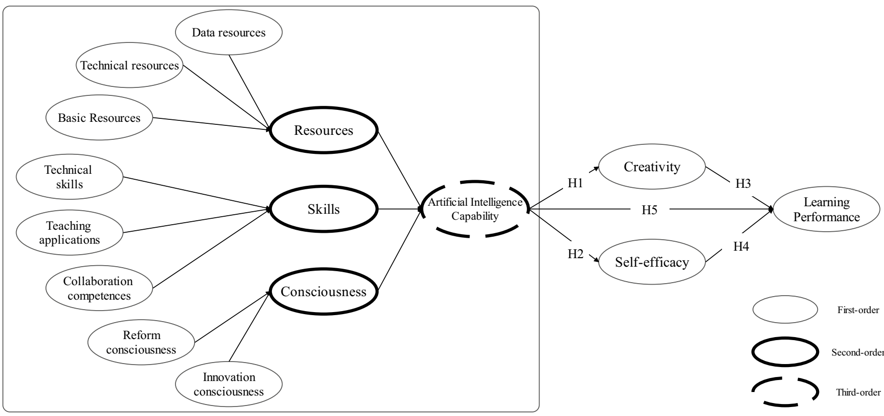

Fig. 2 Conceptual model

3 Methodology

3.1 Instrument

Since this study contains latent variables that cannot be directly observed, it will be measured using a developed scale (Alghamdi et al., 2020; Hair et al., 2022; Wei & Chou, 2020). A total of one formative third-order construct, three formative second-order constructs, and eight reflective first-order variables were included in the research model of the AIC's impact on students' creativity and learning performance in HEIs. The questionnaire was designed to ensure the content validity of the study by using established scales that have been validated by previous research (Wang et al., 2021b). The learning performance measure was adapted from McGill and Klobas (2009); the self-efficacy measure was adapted from Pituch and Lee (2006); the creativity measure was accustomed from Abu-Al-Aish and Love (2013) and Wang and Huang (2020); the measure of AIC was conformed from Mikalef and Gupta (2021). A total of 11 latent variables were included in this questionnaire; each latent variable contained three measurement items and was investigated using a five-level Likert scale (Wei & Chou, 2020).

In completing the questionnaire design about the literature and research framework, this study conducted a pre-survey to assess the quality of the questionnaire. (McGill & Klobas, 2009). To ensure that the respondents accurately understood and completed the questionnaire, we invited twenty university students, teachers, administrators, and academics with relevant research experience to participate in the pre-survey. We collected feedback through questionnaires and one-on-one interviews. Then, we released the modified questionnaire without possible ambiguities, inaccurate wording, and difficult-to-understand questions (Wang et al., 2021a).

3.2 Data collection and samples

Some HEIs in China have started to apply AI to predict keynotes and difficulties of courses, academic performance, and personalized learning suggestions (Wang et al., 2021a). The purposive (judgment) sampling technique helps improve the research results' theoreticality and trustworthiness (Sharma, 2017; Uzir et al., 2021) while facilitating access to participants and data collection (Campbell et al., 2020; Salloum et al., 2019), and has been used widely in quantitative research (Anggraeni & Sole, 2020; Pratama et al., 2020; Yustina et al., 2021). To achieve the objectives of this research and the smooth conduct of the questionnaire, we have two criteria for the selection of participants (Uzir et al., 2021): The first criterion is that the HEI has applied artificial intelligence in at least one aspect of teaching, learning, management, etc. The second criterion is that the respondents have used these AI-based services or products. Then, this study uses purposive (judgment) sampling to select four universities that have applied AI and collect data online (McGill & Klobas, 2009; Mikalef & Gupta, 2021). The questionnaire was created through Questionnaire Star, and the QR code and link to the survey invitation were generated and sent to the participants. We invited teachers from four Chinese universities to collect data (Wang et al., 2021a). After lessons, teachers transmitted the QR code to students through WeChat and QQ groups. Students have noticed the purpose of the survey in advance and can stop answering at any time (Hair et al., 2022). The questionnaire collection took four weeks, and we received 624 results. After completing the filtration, we obtained 561 valid questionnaires (89.9% effective rate) by withdrawing invalid questionnaires with short response times and consistent answers (Abu-Al-Aish & Love, 2013). Individual characteristics of the survey sample data (see Table 3) are also considered in this study. For example, the learning performance of males was significantly worse than that of females because they paid more attention to the competition and ignored the content (Yeo et al., 2022). Students with lower education backgrounds could only complete assigned tasks partly due to limited cognitive development (Saxena et al., 2020). Significant differences also existed in course learning due to insufficient corresponding prior knowledge (Syukur, 2021).

3.3 Data analysis

The measured conceptions in this study contain formative and reflective concepts; the conceptual model proposed in this study is complex and involves a prediction component. Given the above reasons, this study will use SmartPLS 3 based on the partial least squares structural equation modelling (PLS-SEM) analysis technique (Hair et al., 2022; Wang et al., 2021a) for data analysis (Hair et al., 2019; Mikalef & Gupta, 2021).

Table 3 Sample characteristics

Information	Characteristics	N	%
Gender	Male	218	38.9
	Female	343	61.1
Educational background	Vocational student	241	43.0
	Undergraduate students	174	31.0
	Postgraduate students and above	146	26.0
Major	Natural Sciences	201	35.8
	Social Sciences	258	46.0
	Humanities	102	18.2

4 Results

4.1 Common method bias

Common method bias (CMB) may bias results (Podsakoff et al., 2003). In this study, procedural and statistical controls were practiced to reduce the impact of CMB. Procedural rules were used to ensure the accuracy of respondents' feedback on the self-report scale by setting non-private survey questions, conducting pre-testing, and explaining the purpose of the survey. Statistical controls were conducted using one-way tests (Lindell & Whitney, 2001). Using the principal component analysis function in SPSS, Harman's one-factor test revealed that the maximum amount of variance explained by the study data did not reach the critical value of 40%. There was no situation where one factor described most of the variance.

4.2 Measurement model evaluation

Content validity, convergent validity, and discriminant validity were applied to test the validity of this study (Hair et al., 2019). This questionnaire's variables and question items were taken from previously published scales. The questionnaire's content had been tested to be correctly understood and answered through a pre-survey; therefore, the content validity of the measurement scale was considered suitable in this study (Hair et al., 2022). Table 4 presents the Cronbach's Alpha, Combined reliability (CR), and Average Variance Extracted (AVE) for each latent variable. The AVE values are more significant than 0.5, indicating good convergent validity for each latent variable (Hair et al., 2019). The reliability of the measured models was obtained by comparing the magnitude of the CR and Cronbach's Alpha with the critical value of 0.7. The measurement results make it clear that the Cronbach's Alpha and CR values for each potential variable are greater than the critical value of 0.7, which indicates that this measurement model has good reliability (Hair et al., 2019). In addition, the discriminant validity was determined by comparing the correlation coefficients between the latent variables with the AVE square root values. In summary, the model was measured and confirmed to have good reliability and validity (content validity, discriminant validity, and convergent validity).

4.3 Formative constructs validation

This research uses SmartPLS 3 to validate formative constructs (Hair et al., 2019). The validation results of the third-order model of AIC are shown in Table 5.

The validation of the higher-order model of AIC offered that the significance between each variable was less than 0.001, which means that AIC is a well-constructed higher-order model. The former AIC model is a third-order variable consisting of three formative second-order constructs: resources (data resources, technical resources, basic resources), skills (technical skills, teaching applications, collaborative competence), and

Table 4 Reliability, convergent validity, and discriminant validity of the model

	Code	DR	TR	BR	TS	TA	CC	RC	IC	CE	SE	LP
Data resources	DR	**n/a**										
Technical resources	TR	0.525	**n/a**									
Basic Resources	BR	0.532	0.527	**n/a**								
Technical skills	TS	0.522	0.556	0.547	**0.895**							
Teaching application	TA	0.513	0.520	0.528	0.519	**0.877**						
Collaborative competence	CC	0.531	0.547	0.514	0.530	0.510	**0.866**					
Reform consciousness	RC	0.518	0.507	0.490	0.488	0.510	0.479	**0.849**				
Innovation consciousness	IC	0.508	0.522	0.525	0.501	0.499	0.494	0.528	**0.884**			
Creativity	CE	0.437	0.407	0.415	0.364	0.353	0.391	0.372	0.419	**0.851**		
Self-efficacy	SE	0.426	0.367	0.400	0.413	0.390	0.351	0.350	0.405	0.310	**0.883**	
Learning performance	LP	0.476	0.446	0.451	0.438	0.421	0.436	0.416	0.449	0.596	0.515	**0.861**
Cronbach's Alpha		**n/a**	**n/a**	**n/a**	0.875	0.850	0.833	0.807	0.861	0.810	0.858	0.825
CR		**n/a**	**n/a**	**n/a**	0.876	0.851	0.833	0.809	0.862	0.813	0.859	0.827
AVE		**n/a**	**n/a**	**n/a**	0.923	0.909	0.900	0.886	0.915	0.888	0.913	0.896

Latent variable AVE square root values are bolded values on the diagonal

Table 5 Formative constructs validation for AIC

Constructs	Measures	Weighting	Significance	VIF
Resources	Data resources	0.338	$p < 0.001$	1.577
	Technical resources	0.419	$p < 0.001$	1.566
	Basic Resources	0.400	$p < 0.001$	1.583
Skills	Technical skills	0.426	$p < 0.001$	1.574
	Teaching application	0.398	$p < 0.001$	1.530
	Collaborative competence	0.389	$p < 0.001$	1.555
Consciousness	Reform consciousness	0.533	$p < 0.001$	1.387
	Innovation consciousness	0.610	$p < 0.001$	1.387
Artificial intelligence capability	Resources	0.529	$p < 0.001$	2.208
	Skills	0.277	$p < 0.001$	2.798
	Consciousness	0.289	$p < 0.001$	2.950

consciousness (reform consciousness, innovation consciousness). The research model of three formative second-order constructs has been validated (Becker et al., 2012; Hair et al., 2022).

4.4 Structural model evaluation

This study constructed structural equation models (PLS-SEM) using partial least squares on the received questionnaire data, and hypothesis testing was performed using Smart-PLS 3 (Hair et al., 2019). Random sampling was conducted using the self-help method (Bootstrapping), and the sample size was set at 5000. The model study results on the impact of AIC on creativity and learning performance in HEIs are shown in Fig. 3. AIC

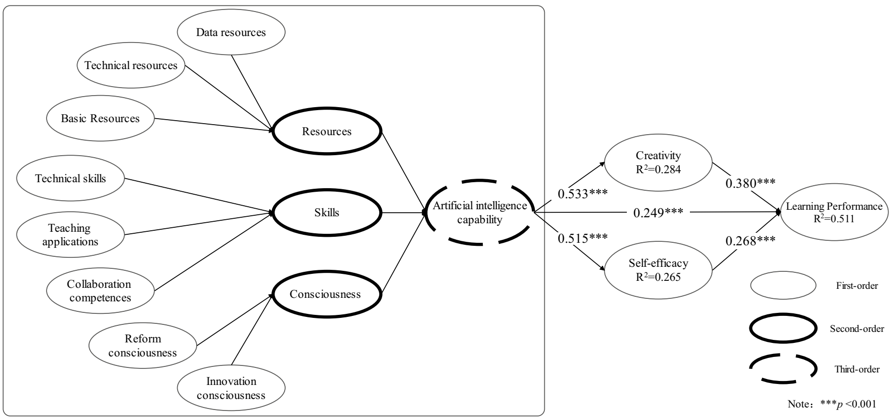

Fig. 3 Results of the structural model

significantly affects students' creativity and self-efficacy; simultaneously, AIC affects learning performance through two mediating variables (creativity and self-efficacy), further revealing that AIC positively impacts learning performance improvement.

Sample Characteristics may affect the reliability of the research results (Pakaja & Wafa, 2021). This study included Gender, Educational background, and Major as control variables in the structural model for testing (Salloum et al., 2019). The data analysis results showed that Gender ($\beta = -0.222$, $p > 0.05$), Educational background ($\beta = 0.029$, $p > 0.05$), and Major ($\beta = 0.018$, $p > 0.05$) did not have a significant effect on the outcome variable (learning performance) (Wu et al., 2022). The results show that HEIs do not need to pay too much attention to students' gender, educational background, and significant effects when deploying AI (Wang et al., 2022).

The R^2 (coefficient of determination) for creativity, self-efficacy and learning performance were 0.284, 0.265, and 0.511, and the overall explanatory power of the research model was 0.511. Thus the model has excellent predictive power for students' learning performance (Hair et al., 2019).

4.5 Mediation

Two mediating paths of creativity and self-efficacy were set up in the research model, and the mediations of the dual paths will be tested with the help of Bootstrapping (Hair et al., 2022).

In the pathway with creativity as the mediating variable, both the direct and indirect effects of AIC on learning performance were significant, suggesting that creativity partially mediates the effect of AIC on learning performance. In the pathway where self-efficacy was the mediating variable, the direct and indirect effects of AIC on learning performance were significant, and self-efficacy partially mediated the path. In summary, creativity and self-efficacy partially mediated the relationship between AIC and learning performance, suggesting that AIC directly affects learning performance and indirectly influences learning performance through creativity and self-efficacy (see Table 6).

Table 6 Mediation analysis

Paths	Effect	95% confidence intervals	Significance	Type
AIC→CE→LP	Direct effect	[0.181,0.343]	Yes	Partial mediation
	Indirect effect	[0.159,0.245]	Yes	
AIC→SE→LP	Direct effect	[0.181,0.343]	Yes	Partial mediation
	Indirect effect	[0.098,0.177]	Yes	

5 Discussion

5.1 Research implications

This research has focused on AI applications within the HEIs, where research regarding AI technologies has been lacking (Mikalef & Gupta, 2021). HEIs' capability of using AI has been concerned to reveal their inequivalence to digital competency and information literacy in education as well as high reliance on resources and technical support, therefore extending the findings of current AI's connotation and definition (Kaplan & Haenlein, 2019; McCarthy, 2007; Tian, 2021).

By providing a theoretical context, Resource-based theory (RBT), for AIC, this study recognizes eight subdivisional latitudes of AIC from tangible and intangible resources, respectively, at the organizational level (Barney et al., 2021). The AIC in HEIs is defined as a higher-order variable consisting of resources (data resources, technical resources, basic resources), skills (technical skills, teaching applications, collaboration competencies), and consciousness (reform consciousness, innovation consciousness). The higher-order model of AIC in HEIs is to have good reliability and validity using partial least structural equation modelling (PLS-SEM) inputting data collected from the questionnaire. The higher-order model of AIC validated by SmartPLS confirms the new explanatory power of resource-based theory in technological practices from previous areas of academic entrepreneurship and human resources (Ma & Dou, 2020; Mikalef & Gupta, 2021).

This study also deconstructs the intrinsic mechanics of AIC. Potential constitutive elements that construct AIC's framework are identified and classified to transform in teaching and learning scenarios. The AIC represented in this paper enriches the finding of Mikalef and Gupta (2021) and Lee and Lee (2021), providing the conceptual basis of the efficiency of manipulating AI in HEIs for future study.

More importantly, this study developed a research model describing how AIC works on learning performance and emphasized the relationship between students' self-efficacy, creativity, and learning performance, which has been overlooked in previous research (Flink & Cooper-Larsen, 2020; Oktradiksa et al., 2021; Li & Wang, 2021). The data analysis showed that AIC influences students' creativity, self-efficacy, and learning performance and that higher levels of AIC have significant effects on these factors. The mediation analysis proves that AIC directly affects students' learning performance; it significantly affects students' creativity and self-efficacy through the findings above. It reveals that AIC enhancement in HEIs can benefit improve students' creativity, self-efficacy, and learning performance. It also suggests that HEIs put effort into a holistic approach to building AIC and implement a comprehensive strategy in resources, technologies, and consciousness to achieve precise results. The empirical analysis discloses that student-related creativity and self-efficacy also positively and significantly influence learning performance. Hence, the research model in this study also provides theoretical support for improving students' creativity and self-efficacy.

5.2 Practical implications

Reserve and deploy artificial intelligence resources, and apply artificial intelligence to improve students' creativity and learning performance. This study found that deploying AI needs to reserve three resources (Data, Technical, and Basic Resources). These three resources provide strategies for HEIs to take the first step in deploying AI. We also demonstrate the positive impact of AIC on student creativity and learning performance (Shan et al., 2021), further demonstrating the significant value of AI deployment in HEIs (Wenge, 2021). Data technical and essential resources are the prerequisites for applying AI to predict academic performance, analyze learning disabilities, and early warning of dropout risks. Therefore, HEIs should also provide support for capital investment. Reserve the resources required for AI to help HEIs enjoy the technological dividends brought about by the development of AI and ultimately improve the quality of education in HEIs.

Improve the digital literacy of teachers and students to meet the rapidly developing digital age. The findings of this study provide an entry point for HEIs to promote the application of AI from three aspects: Technical skills, Teaching application, and Collaborative competence. AI service applications such as personalized recommendation, automatic evaluation of spoken language, and automatic grading of papers also require teachers and students to have basic digital literacy (Wang & Zhan, 2021). Both teachers and students should have the opportunity to train and apply AI services or products, and HEIs can also provide relevant digital courses and learning support for teachers and students to help teachers and students better understand and apply AI products. In particular, teachers may use artificial intelligence analysis, prediction, intervention, and other technologies in their teaching process to help them identify students who need additional assistance and improve their creativity and learning performance. HEIs should try to establish a mechanism for communication and cooperation. The early use of AI will cause many technical problems (Paek & Kim, 2021), which cannot be separated from the cooperation between users and technical departments.

Cultivate a positive atmosphere of innovation and further reform, and use artificial intelligence technology to foster innovation awareness among teachers and students. Promote new AI-based services or products and ultimately allow students and teachers to gain the benefits of applying AI from authentic problem-solving on a daily basis (Chen et al., 2022). Managers of HEIs should also take the initiative to study the latest articles and courses related to AI. Remove the ideological burden for HEIs to apply artificial intelligence technology, and hold relevant workshops, forums, and competitions (Xu, 2021) to obtain more innovative cases of AI applications.

5.3 Limitations and future research

Based on the extensive paper, questionnaire, and empirical analysis, this study investigates the connotation and components of AIC. It verifies the relationship between AIC on students' creativity, self-efficacy, and learning performance in HEIs. However, this study has some limitations due to the constraints of objective conditions. First, the data obtained by the purposive (judgment) sampling technique helps to strengthen the theory's test. It improves the theoreticality of the research conclusions (Baek & Morimoto, 2012; Sharma, 2017; Uzir et al., 2021), but the data are mainly from four universities in China, which is challenging to represent the situation of HEIs in different countries. Second, this study proposes a model for the application of AI in HEIs, without considering the impact of artificial intelligence application fields, and artificial intelligence applications in different situations may have other effects. The third is that a single type of respondent may have a certain one-sidedness, and it is challenging to represent the opinions of teachers and administrators.

Therefore, future studies can consider more sample sources and data sampling methods to expand the applicability of the results of this study. In addition, in-depth research can be conducted in the future based on different AI application scenarios to obtain more detailed insights. Given the complexity of AIC, it is possible to consider conducting research from multiple perspectives, including students, teachers, and administrators, to further enrich the diverse conclusions of this research topic.

6 Conclusion

Artificial intelligence technology plays a vital role in social and educational development with growing interest and investigation (Tan, 2020; UNESCO, 2021). In particular, the deep integration of AI and education is a widespread issue for many education practitioners and a concern for the government at all levels (Shan et al., 2021; Wenge, 2021). This study outlines the connotations and components of artificial intelligence capability at the HEI level through an extensive collection and analysis of relevant research results, combined with questionnaire surveys and empirical analysis. We analyzed eight sub-dimensions of resources (data resources, technical resources, basic resources), skills (technical skills, teaching applications, collaboration competencies), and consciousness (reform consciousness, innovation consciousness) based on RBT (Lee & Lee, 2021; Paek & Kim, 2021; Shan et al., 2021; Wenge, 2021). In addition, this study also validates the dual mediation model that artificial intelligence capability in the HEI affects learning performance through two mediating variables (creativity and self-efficacy) (Koć-Januchta et al., 2020). It proves that artificial intelligence capability in higher education institutes positively affects students' creativity and self-efficacy in learning performance (Li & Wang, 2021). Based on these findings, this study also explores theoretical and practical implications for developing artificial intelligence capability in higher education institutes to enhance students' creativity, self-efficacy, and learning performance (Paek & Kim, 2021).

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Declarations

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