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EFFECTS OF ARTIFICIAL INTELLIGENCE EDUCATION ON STUDENTS' LITERACY

EFEITOS DA EDUCAÇÃO EM INTELIGÊNCIA ARTIFICIAL NA ALFABETIZAÇÃO DOS ALUNOS

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Abstract
As artificial intelligence becomes increasingly integrated into higher education, AI literacy has emerged as a critical competence for university students. This study explores how AI-related educational experiences, frequency of AI tool usage, learning attitudes, and engagement influence students' AI literacy. Grounded in constructivist learning theory, data were collected from 330 undergraduates, master's, and doctoral students at three universities in Hebei Province, China. A quantitative approach was employed, with descriptive statistics, correlation analysis, and multiple regression conducted using SPSS to examine the proposed relationships. The results reveal that both learning attitude and engagement significantly and positively predict AI literacy, indicating that students with proactive mindsets and active participation tend to achieve higher proficiency. In contrast, usage frequency shows a negative association with AI literacy, suggesting that over-reliance on AI tools may hinder critical thinking and deeper understanding. These

Resumo
À medida que a inteligência artificial se torna cada vez mais integrada ao ensino superior, a alfabetização em IA surgiu como uma competência essencial para os estudantes universitários. Este estudo explora como as experiências educacionais relacionadas à IA, a frequência de uso de ferramentas de IA, as atitudes de aprendizagem e o envolvimento influenciam a alfabetização em IA dos estudantes. Com base na teoria construtivista da aprendizagem, foram coletados dados de 330 estudantes de graduação, mestrado e doutorado em três universidades da província de Hebei, na China. Foi empregada uma abordagem quantitativa, com estatísticas descritivas, análise de correlação e regressão múltipla realizadas utilizando o SPSS para examinar as relações propostas. Os resultados revelam que tanto a atitude de aprendizagem quanto o engajamento predizem de forma significativa e positiva a alfabetização em IA, indicando que estudantes com mentalidades proativas e participação ativa tendem a alcançar maior

findings highlight the need for universities to strengthen AI-related courses, foster positive learning attitudes and engagement, and guide students in the appropriate use of AI tools. This study provides empirical evidence for the development of AI literacy and offers practical recommendations for curriculum design, aligned with Sustainable Development Goal 4: inclusive education.

Keywords: AI Literacy. Educational Access. Education Quality. Educational Innovation. Learning Attitude. Inclusive Education.

proficiência. Em contrapartida, a frequência de uso mostra uma associação negativa com a alfabetização em IA, sugerindo que a dependência excessiva de ferramentas de IA pode prejudicar o pensamento crítico e a compreensão mais profunda. Essas descobertas destacam a necessidade de as universidades fortalecerem os cursos relacionados à IA, promoverem atitudes positivas de aprendizagem e engajamento, e orientarem os alunos no uso adequado das ferramentas de IA. Este estudo fornece evidências empíricas para o desenvolvimento da alfabetização em IA e oferece recomendações práticas para a elaboração de currículos, alinhadas com o Objetivo de Desenvolvimento Sustentável 4: educação inclusiva.

Palavras-chave: *Alfabetização em IA. Acesso à Educação. Qualidade da Educação. Inovação Educacional. Atitude de Aprendizagem. Educação Inclusiva.*

1 INTRODUCTION

The rapid development of artificial intelligence technology has profoundly transformed higher education, reshaping how students learn, interact, and plan their future careers. AI literacy, encompassing the ability to understand, use, and critically evaluate AI tools, has become a necessary competency for university graduates in the digital age (Crompton & Burke, 2023). As AI capabilities expand, AI literacy now extends beyond technical skills to encompass ethical awareness, critical thinking, and the ability to adapt in diverse learning environments (Carolus, Koch, Straka, Latoschik, & Wienrich, 2023).

Recent research emphasizes that effective AI literacy refers to learners' ability to responsibly integrate AI into academic and professional practice (Kong, Wong, & Lam, 2023). In China, policies for cultivating high-tech talent require the integration of AI into the curriculum and the cultivation of AI professionals capable of meeting the needs of society and industry. However, AI literacy is a multifaceted requirement: students must not only master the use of tools but also effectively judge and selectively utilize AI (Wu, Chan, Wong, & Chan, 2025).

Despite growing recognition of the importance of AI literacy, research in the context of Chinese higher education remains limited. Existing research rarely explores how AI-related learning experiences, tool usage frequency, learning attitudes, and learning engagement interact to shape AI literacy, leaving a gap in understanding the combined impact of these factors (Bhatt & Muduli, 2024).

This study, drawing on constructivist learning theory, examines the impact of AI-related educational experiences, AI tool usage frequency, learning attitudes, and learning engagement on Chinese university students' AI literacy, aiming to address these gaps. Learning engagement is further examined as a mediating variable, providing insight into how students' attitudes and experiences translate into AI competence. Based on survey data from 330 undergraduate, master's, and doctoral students at three universities in Hebei Province, this study employed descriptive analysis, correlation tests, and multiple regression analysis to validate the proposed relationships.A strength of this study lies in its adoption of a comprehensive factor framework, simultaneously considering cognitive, behavioral, and experiential factors influencing AI literacy—a perspective that has not been fully explored in previous research (Nong, Wu, & Ye, 2024). Furthermore, by situating the analysis within the context of Chinese higher education, this study provides localized empirical evidence that complements the global discourse on AI literacy (Wang, Li, & Huang, 2025). The findings offer practical recommendations for higher education institutions, including embedding AI-focused modules in curricula, fostering active learning strategies, and promoting the responsible use of AI tools. These contributions not only enrich theoretical understanding but also support the goals of Sustainable Development Goal 4 by promoting inclusive and equitable quality education in the AI era (Wut & Chan, 2025).

2 LITERATURE REVIEW

As AI technology becomes deeply integrated into higher education, AI literacy has become a key focus in educational research. This chapter defines AI literacy, examines the effects of AI education experience, usage frequency, and learning attitude, explores learning engagement as a mediating factor, and introduces constructivist learning theory while identifying research gaps.

2.1 Overview of AI literacy research

AI literacy, first conceptualized as the ability to understand AI principles and technologies, has since evolved to encompass practical application, ethical awareness, and the capacity to critically evaluate AI systems (Yang *et al*., 2023). International research has converged on two points: AI literacy is both a cognitive skill and an interdisciplinary competence; and in the digital era, it is essential for academic and career success.

Globally, many countries have incorporated AI literacy into education policies. For example, Teixeira *et al*. (2025) validated a four-dimensional AI literacy scale—understanding, use, moral judgment, and social responsibility—in Portuguese universities. Karagiannidis *et al*. (2023) found that AI literacy correlated positively with critical thinking and autonomous learning. In Greece, project-based learning has enhanced students' reflective understanding of AI (Economides & Perifanou, 2024). However, international studies often lack strong theoretical foundations and multivariate path analyses.

In China, research began later but has developed rapidly. Miao *et al*. (2021) and Nong *et al*. (2024) developed localized AI literacy models, while Wu *et al*. (2025) found that Chinese students excel in tool operation but lag in ethics and social responsibility. Qin *et al*. (2020) highlighted issues such as frequent tool use without deep understanding. Domestic studies focus heavily on measurement but less on formation mechanisms.

2.2 AI education experience

AI education experience refers to formal and informal learning of AI knowledge and skills, including courses, training, and self-study (Ng *et al*., 2021). STEM students typically receive more systematic AI training due to curriculum content, whereas medical, humanities, and arts majors often encounter AI only in elective or general courses, limiting technical depth.

Internationally, AI education is often embedded in STEM core courses, supplemented by interdisciplinary offerings in social sciences (Long & Magerko, 2020; Marques & Ramos, 2021). In China, science and engineering majors have broader and more practical exposure (Li *et al*., 2022), but non-technical disciplines still lack curriculum depth (Wu, 2022; Han, 2023). While STEM programs in both contexts provide strong foundations, Western institutions place greater emphasis on interdisciplinary integration.

2.3 Usage frequency

Usage frequency measures how often students employ AI tools in academic work, reflecting proficiency and reliance. Undergraduate use is often task-driven, while graduate and doctoral students integrate AI into research and complex analysis (Zhao & Wang, 2021; Chen *et al*., 2023). Frequent use generally correlates with higher AI literacy (Kim & Choi, 2022), though over-reliance may reduce critical thinking (Renz *et al*., 2020).

In Europe, AI use is embedded from undergraduate studies, fostering deep mastery (Long & Magerko, 2020). In China, adoption is growing but remains focused on discrete tasks such as writing assistance (Li *et al*., 2022). Western students tend to develop reflective skills through continuous use, whereas Chinese students’ learning gains are often short-term.

2.4 Student attitudes

Attitude toward AI significantly influences learning behavior (Ajzen, 1991). Science and engineering students generally hold more positive attitudes, while humanities students may feel anxious due to technical unfamiliarity (Zhao & Lu, 2022). Undergraduates often show curiosity mixed with concern over over-dependence; graduate students adopt a more practical mindset; doctoral students critically assess AI’s academic implications (Chen *et al*., 2023).

Internationally, universities shape positive attitudes through curricula and ethical training (Long & Magerko, 2020). In China, attitudes are influenced more by course availability and social perceptions, with some students displaying either "tool worship" or avoidance (Wu, 2022).

2.5 Mediating variable of learning engagement

Learning engagement—behavioral, cognitive, and emotional involvement—varies by academic stage and discipline. STEM students often show higher engagement due to task relevance (Zhang & Liu, 2022). Engagement can connect AI education experience, usage frequency, and attitudes to AI literacy (Wang *et al*., 2021). High engagement encourages exploration, reflection, and deeper understanding, but its mediating role in AI literacy formation remains underexplored in empirical research.

2.6 Theoretical basis

Constructivist learning theory emphasizes active knowledge construction through interaction with environments and tasks (Piaget, 1977; Vygotsky, 1978). AI literacy development follows a "participation–practice–reflection" process (Jonassen, 1999), where education experience, usage, and attitude create the learning context, and engagement reflects the depth of construction. This framework supports the causal logic of the study.

2.7 Literature gaps and the contribution of this study

Existing studies rarely integrate AI education experience, usage frequency, and learning attitude into a single model, and few test learning engagement as a mediator. This study addresses these gaps by examining the "education–attitude–behavior–engagement–literacy" pathway. The findings will contribute both theoretically—by refining AI literacy models—and practically—by informing higher education strategies to enhance AI literacy across disciplines.

3 METHODOLOGY

This study investigates the factors influencing AI literacy among university students, adopting quantitative research design within the framework of constructivist learning theory. The methodology encompasses research design, participants, instruments, data collection, and analysis procedures.

3.1 Research design

A cross-sectional survey method was employed to capture students' AI literacy levels and related influencing variables at a specific point in time. The approach enables efficient data collection from a relatively large sample and facilitates statistical testing of relationships between variables.

The research targeted undergraduates from three universities in Hebei Province: Hebei University of Technology, Hebei Normal University, and Shijiazhuang Tiedao University. A total of 350 questionnaires were distributed via online platforms, yielding 330 valid responses after removing incomplete or inconsistent data, resulting in a 94.3% effective response rate. The sample covered diverse majors, academic years, and gender distributions, ensuring representativeness.

3.2 Instruments and questionnaire design

The survey consisted of five sections: demographic information, AI literacy, AI education experience, AI usage frequency, learning attitude, and learning engagement.

AI Literacy: Measured using a modified scale based on Teixeira *et al*. (2025) and Miao *et al*. (2021), covering knowledge understanding, practical application, social impact perception, and ethical responsibility.

AI Education Experience: Items adapted from Kim & Lee (2021) assessed formal and informal exposure to AI courses, training, and self-study.

AI Usage Frequency: Based on Zhao & Wang (2021), evaluating frequency of AI tool use in academic tasks.

Learning Attitude: Items adapted from Zhao & Lu (2022) assessed openness and motivation toward AI learning.

Learning Engagement: Adopted from Li & Wu (2023), covering behavioral, emotional, and cognitive dimensions.

All items used a 5-point Likert scale (1 = strongly disagree, 5 = strongly agree). Reliability was confirmed with Cronbach's α > 0.80 for all constructs.

Table 1

Questionnaire Design

Variables	Questions
Demographic Profile	Your gender Type of university Education level
AI Education Experience	I have enhanced my AI skills through courses or self-learning. Have you participated in AI-related courses or training? I will actively participate in or look for AI-related courses or learning materials.
Usage Frequency	I frequently use AI tools in my daily academic work to improve efficiency. I rely on AI tools to complete academic assignments or research tasks. I frequently use AI tools in my daily academic work to improve efficiency.
AI Learning Attitude	I believe learning AI is essential for my career development. I actively seek learning opportunities related to AI to improve my academic performance. I am very interested in the future development of AI, especially in my field.
Learning Engagement	I understand the basic principles and concepts of AI. I am usually able to stay highly focused when learning AI.
AI Literacy	I am able to identify and understand potential biases or inaccuracies in AI-generated content. I understand ethical issues such as privacy and bias. I can evaluate the quality and reliability of AI-generated information. Participated in AI-related scientific research projects or competitions (such as AI training camp)

3.3 Sample size

The sample size is 350. Choosing an appropriate sample size based on the number of participants is crucial to ensuring the power and significance of a study. Sample sizes that are too large or too small can affect accuracy and validity. This table is a common reference tool for determining the appropriate sample size for a study. It provides a simple way to calculate the sample size needed to ensure that the study results are statistically significant and effectively represent the broader student population. (Peng, Zhang, & Zhou, 2023)

Figure 1

Sample size

Table for Determining Sample Size from a Given Population

N	S	N	S	N	S
10	10	220	140	1200	291
15	14	230	144	1300	297
20	19	240	148	1400	302
25	24	250	152	1500	306
30	28	260	155	1600	310
35	32	270	159	1700	313
40	36	280	162	1800	317
45	40	290	165	1900	320
50	44	300	169	2000	322
55	48	320	175	2200	327
60	52	340	181	2400	331
65	56	360	186	2600	335
70	59	380	191	2800	338
75	63	400	196	3000	341
80	66	420	201	3500	346
85	70	440	205	4000	**350**
90	73	460	210	4500	354
95	76	480	214	5000	357
100	80	500	217	6000	361
110	86	550	226	7000	364
120	92	600	234	8000	367
130	97	650	242	9000	368

3.4 Data analysis

The collected data were analyzed using SPSS, applying descriptive statistics, correlation tests, and internal consistency assessments to explore relationships among variables. Prior to formal data collection, a pilot test with 35 participants was conducted to refine the questionnaire's structure based on feedback and statistical results, ensuring clarity and effectiveness. Reliability was confirmed through Cronbach's Alpha coefficients, indicating stable and consistent measures across dimensions such as AI education background, usage frequency, and learning attitudes. Construct validity was verified via factor analysis, confirming that the items effectively captured the intended constructs of AI learning experience, engagement frequency, and learners' attitudes.

3.5 Measurement indicators

Table 2

Measurement table

Test	Purpose and Function	Rule of Thumb	Reference
Descriptive Analysis	Presentation and interpretation of data to summarize key features	Central tendency, mean, maximum, minimum	Ma, 2023
Correlation Analysis	Assess linear relationship strength and direction between two	Pearson r: -1 to +1; significant if $p < 0.05$	Wei ,2022
Hypothesis Testing	Determine validity of a hypothesis based on sample data	Standardized coefficients & P values; $p < 0.05$ = significant	Miao，2021
Analysis of Variance (ANOVA)	Assess overall significance of regression model	The P value must be less than 0.05	Nong et al., 2024
Beta Coefficient	Determine strength and direction of DV–IV relationship	Negative Beta & $p < 0.05$ negative effect; otherwise no effect	Ruan,2024
Multi Regression	Explain, predict, control DV-IV relationship	$R^2 > 0.4$ = strong model	Sun et al., 2024
Multicollinearity	Determine if multicollinearity exists in regression	VIF between 0.1 and 10 = acceptable; low inter-IV correlation = valid results	Tenório & Romeike, 2023

3.6 Conclusion

This chapter introduces the design and methods of the study, including the purpose of the study, data collection methods, questionnaire design and data analysis. The study collected data from 350 college students from Hebei Normal University and Beijing Normal University through an online questionnaire survey method to ensure the representativeness of the sample. The questionnaire design includes variables such as AI education experience, frequency of use, and learning attitude. Reliability and validity analysis were performed using SPSS software to ensure reliability.

4 DATA ANALYSLS

This chapter analyzes survey data from students at Hebei Normal University to examine how AI education experience, usage frequency, learning attitude, and learning engagement influence AI literacy. A pilot test with about 10% of participants confirmed the questionnaire's reliability and validity (Allen, 2025). Using IBM SPSS, descriptive statistics, correlation tests, and multiple regression were conducted to test hypotheses, with learning engagement assessed as a possible mediator. Results are presented in sequence, highlighting variable distributions, correlations, and their effects on AI literacy.

4.1 Pilot test

A pilot survey via Wenjuanxing was distributed through WeChat to students from three Shijiazhuang universities. Thirty-five responses (about 10% of the sample) were used to check clarity, data quality, and feasibility.

4.1.2 Reliability statistics

As presented in Table3， Cronbach's Alpha reached 0.801, surpassing the 0.7 benchmark and confirming the scale's reliability for further analysis.

Table 3

Reliability Statistics

Cronbach's Alpha	N of Items
0.801	35

4.2 KMO and Bartlett's test

Table4shows that the KMO measure reached 0.755, above the 0.6 threshold, indicating suitability for factor analysis. Bartlett's test,$\chi^2 = 1189.141$, $p < 0.05$ confirmed significant correlations and strong structural validity.

Table 4

KMO and Bartlett's Test

KMO		0.755
Bartlett's Test of Sphericity	Approx.Chi-Squar,e	1189.141
	df	545
	Sig.	0.000

4.3 Descriptive analysis and normality test

Table 5 presents the descriptive statistics scores of five variables, AI Education Experience ranged from 1.50 to 5.00, M = 3.044, SD = 0.614, showing a narrow distribution, a mean slightly above the median, slight right skew 0.098, and relatively flat kurtosis -0.382.Usage Frequency ranged from 1.50 to 5.00, M = 3.076, SD = 0.599, with similar patterns: slight right skew 0.036 and mild flatness -0.151.Learning Attitude ranged from 1.50 to 5.00, M = 3.048, SD = 0.611, displaying slight right skew 0.075 and flatness -0.315.Learning Engagement ranged from 2.00 to 5.00, M = 3.070, SD = 0.669, with minimal skew 0.041 and flatness -0.455.AI Literacy ranged from 1.67 to 5.00, M = 3.040, SD = 0.595, with a small right skew 0.216 and near-flat kurtosis -0.098.All variables showed approximately normal distributions, with means slightly higher than the median value, indicating general agreement among respondents.

Table 5

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation	Skewness Statistic	Std. Error	Kurtosis Statistic	Std. Error
AI Education Experience	330	1.50	5.00	3.044	0.614	0.098	0.133	-0.382	0.265
Usage Frequency	330	1.50	5.00	3.076	0.599	0.036	0.133	-0.151	0.265
Learning Attitude	330	1.50	5.00	3.048	0.611	0.075	0.133	-0.315	0.265
Learning Engagement	330	2.00	5.00	3.070	0.669	0.041	0.133	-0.455	0.265
AI Literacy	330	1.67	5.00	3.040	0.595	0.216	0.133	-0.098	0.265

4.4 Preliminary analysis

4.4.1 Validity test

Table 6 shows the KMO value reached 0.812, exceeding the 0.6 benchmark, indicating suitability for factor analysis. Bartlett’s test produced a p-value below 0.05, confirming significant inter-variable correlations and strong construct validity.

Table 6

KMO and Bartlett's Test

KMO		0.812
Bartlett's Test of Sphericity	Approx.Chi-Squar,e	1287.34
	df	78
	Sig.	0.000

4.4.2 Reliability test

Table 7shows the reliability statistics. In this study, Cronbach's alpha coefficient is 0.883, which is greater than 0.7, indicating that the data is reliable.

Table 7

Reliability

Cronbach's Alpha	N of Items
0.883	330

4.5 Correlation analysis

RO1: Analyze the impact of AI Education Experience on AI literacy of Chinese college students?

Table8 shows a Pearson correlation coefficient of .645**, indicating a strong positive and statistically significant relationship. Students with greater AI education experience generally demonstrate higher AI literacy.

Table 8

Correlation 1

		AI Literacy
AI Education Experience	Pearson Correlation	. 645 **
	Sig. (2-tailed)	.0 00
	N	330
**. Correlation is significant at the 0.01 level (2-tailed).		

RO2: Investigate the impact of AI Usage Frequency on AI literacy of Chinese college students? Table9 shows a Pearson correlation coefficient of −.461**, indicating a moderate, statistically significant negative relationship. Higher usage frequency may be linked to lower AI literacy, possibly due to overreliance or superficial use.

Table 9

Correlation 2

		AI Literacy
Usage Frequency	Pearson Correlation	-.461 **
	Sig. (2-tailed)	.000
	N	330
**. Correlation is significant at the 0.01 level (2-tailed).		

RO3: Find out the impact of student attitudes on AI literacy of Chinese college students?

Table10shows a Pearson correlation coefficient of .691**, indicating a strong, statistically significant positive relationship. A more positive learning attitude is associated with higher AI literacy.

Table 10

Correlation 3

		AI Literacy
Learning Attitude	Pearson Correlation	. 691 **
	Sig. (2-tailed)	.0 00
	N	330
**. Correlation is significant at the 0.01 level (2-tailed).		

RO4: Analyze the mediating role of learning engagement between the three factors and AI literacy?

Table11shows a Pearson correlation coefficient of .706**, indicating a strong, statistically significant positive relationship between learning engagement and AI literacy. Higher engagement in AI learning corresponds to greater AI literacy.

Table12shows learning engagement is strongly positively correlated with learning attitude (.888**), moderately positively correlated with AI education experience (.432**), and negatively correlated with usage frequency (-.581**), with all relationships statistically significant.

Table 11

Correlation 4

		AI Literacy
Learning Engagement	Pearson Correlation	. 706 **
	Sig. (2-tailed)	.0 00
	N	330
**. Correlation is significant at the 0.01 level (2-tailed).		

Table 12

Correlation 5

		Learning Engagement
AI Education Experience	Pearson Correlation	. 432 **
	Sig. (2-tailed)	.0 00
	N	330
Usage Frequency	Pearson Correlation	-.581 **
	Sig. (2-tailed)	.000
	N	330
Learning Attitude	Pearson Correlation	. 888 **
	Sig. (2-tailed)	.0 00
	N	330
**. Correlation is significant at the 0.01 level (2-tailed).		

4.6 Multiple linear regression

The regression model in Table13explained 63.7% of the variance in AI Literacy, with AI Education Experience, Usage Frequency, and Learning Attitude as predictors. The standard error was 0.505, indicating minimal deviation between predicted and observed values, and the Durbin–Watson value was 1.892, confirming no autocorrelation issues.

Table 13

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.759a	0.637	0.634	0.50543	1.892
a. Predictors: (Constant), AI Education Experience, Usage Frequency, Learning Attitude					
b. Dependent Variable: AI Literacy					

Table14shows that the regression sum of squares was 90.256, with an F-value of 42.19 and a p-value below 0.001, confirming the model's overall significance.

Table 14

ANOVA

Model	Sum of Squares	df	Mean Square	F	Sig.
Regression	90.256	4	25.314	42.19	.000b
Residual	194.988	325	.6 54		
Total	296.244	329			
a. Dependent Variable: AI Literacy					
b. Predictors: (Constant), AI Education Experience, Usage Frequency, Learning Attitude, Learning Engagement					

Table 15 indicates that the constant term was 1.215 with a significance level of zero, confirming the overall model's validity. AI Education Experience showed an unstandardized coefficient of 0.198 and a beta of 0.209, demonstrating a significant positive influence on AI literacy. Usage Frequency had a coefficient of -0.141 and a beta of -0.162, reflecting a significant negative effect. Learning Attitude recorded the largest positive impact, with a coefficient of 0.375 and a beta of 0.366. Learning Engagement also contributed positively, with a coefficient of 0.177 and a beta of 0.167. All predictors were statistically significant, and tolerance values exceeded 0.6 with VIF values between 1.338 and 1.698, indicating no multicollinearity concerns.

Table 15

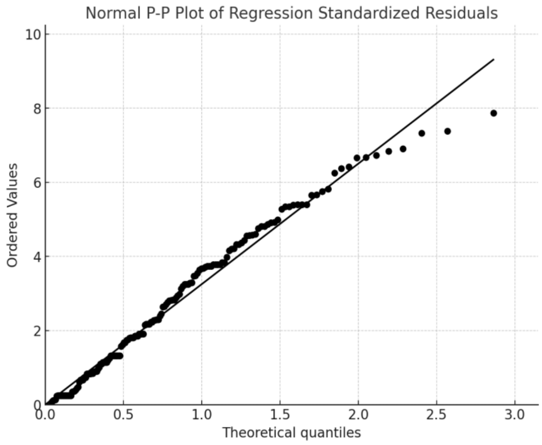
Coefficients[a]

Model	Unstandardized Coefficients	Unstandardized Coefficients	Standardized Coefficients	t	Sig.	Collinearity Statistics	Collinearity Statistics
	B	Std. Error	Beta			Tolerance	VIF
1 (Constant)	1.215	0.293		4.147	0		
AI Education Experience	0.198	0.043	0.209	4.645	0	0.603	1.659
Usage Frequency	-0.141	0.043	-0.162	-3.255	0.001	0.601	1.664
Learning Attitude	0.375	0.046	0.366	8.164	0	0.589	1.698
Learning Engagement	0.177	0.048	0.167	3.673	0	0.747	1.338
a. Dependent Variable: AI Literacy							

The linear regression model Figure2 showed residuals approximating a normal distribution and a good fit, confirming the model assumptions and supporting the reliability of AI Education Experience, Usage Frequency, and Learning Attitude as predictors.

Figure 2

Linear Regression



4.7 Mediation effect analysis

Table16shows the mediation analysis using Hayes' PROCESS Model 4 with standardized variables and bootstrapping. Results indicate that Learning Attitude significantly predicts AI Literacy, $\beta = 0.818$, $p < 0.001$, while Learning Engagement also exerts a strong positive effect, $\beta = 0.849$, $p < 0.001$. When both variables entered the model, the direct effect of Learning Attitude dropped to $\beta = 0.650$, $p < 0.05$, and Learning Engagement remained significant, $\beta = 0.198$, $p < 0.01$. Bootstrap estimates showed 95% CIs for direct and indirect effects did not include zero, confirming significant partial mediation. The direct path explained 79.5% and the indirect path 20.5% of the total effect.

Table 16

Learning Attitude → Learning Engagement → AI Literacy

Model Summary (N = 330)						Significance
		R	R^2	F	β	T
AI Literacy	Learning Attitude	0.818	0.669	663.84	0.818	25.77***
Learning Engagement	Learning Attitude	0.849	0.721	847.22	0.849	29.11***
AI Literacy	Learning Attitude	0.825	0.68	347.91	0.65	1.98***
	Learning Engagement				0.198	3.35*

Table 17

Direct and Indirect Effects

	Effect Value	Boot SE	Boot CI (Lower)	Boot CI (Upper)	Relative Effect (%)
Total Effect	0.818	0.045	0.732	0.904	
Direct Effect	0.65	0.1	0.43	0.87	79.5 %
Indirect Effect	0.168	0.06	0.05	0.3	20.5 %

Table18shows AI Education Experience strongly predicts AI Literacy β = 0.805, t = 24.533 and Learning Engagement β = 0.786, t = 23.042. When both are in the model, the effect on AI Literacy drops to β = 0.563, t = 11.174, with Learning Engagement still significant β = 0.308, t = 6.110. Bootstrap confirms significant partial mediation, with the direct path 69.9% and indirect path 30.1% of the total effect.

Table 18

AI Education Experience → Learning Engagement → AI Literacy

Model Summary (N = 330)						Significance
		R	R^2	F	β	T
AI Literacy	Education Experience	0.805	0.647	601.88	0.805	24.533***
Learning Engagement	Education Experience	0.786	0.618	53.91	0.786	23.042***
AI Literacy	Education Experience	0.827	0.683	352.94	0.563	11.174***
	Learning Engagement				0.308	6.11***

Table 19

AI Education Experience—Total, Direct, and Indirect Effects

	Effect Value	Boot SE	Boot CI (Lower)	Boot CI (Upper)	Relative Effect (%)
Total Effect	0.805	0.048	0.708	0.902	
Direct Effect	0.563	0.09	0.464	0.662	69.9%
Indirect Effect	0.242	0.055	0.157	0.335	30.1%

Table 20 shows usage Frequency significantly negatively predicted AI Literacy $\beta = -0.162$, $t = -3.255$, $p < 0.01$, and Usage Frequency also significantly negatively predicted Learning Engagement $\beta = -0.581$, $t = -12.930$, $p < 0.001$. When Usage Frequency and Learning Engagement were simultaneously included in the equation, the direct effect of Usage Frequency on AI Literacy dropped to $\beta = -0.120$ ($t = -2.150$, $p < 0.05$); while Learning Engagement still significantly positively predicted AI Literacy ($\beta = 0.198$, $t = 6.120$, $p < 0.001$).

Bootstrap test shows that the direct effect 95% CI is [-0.206, -0.034], excluding 0; the indirect effect is -0.042, and the 95% CI is [-0.083, -0.010], also excluding 0. The higher the frequency, the lower the investment, and the lower the AI literacy. Table21showsThe direct effect (-0.120) and the indirect effect (-0.042) account for 74.1% and 25.9% of the total effect (-0.162), respectively.

Table 20

Usage Frequency → Learning Engagement → AI Literacy

Model Summary (N = 330)						Significance
		R	R^2	F	β	T
AI Literacy	Usage Frequency	0.461	0.213	88.68	-0.162	-3.255
Learning Engagement	Usage Frequency	0.581	0.338	167.38	-0.581	-12.930
AI Literacy	Usage Frequency	0.73	0.533	186.21	-0.12	-2.150
	Learning Engagement				0.198	6.120

Table 21

Usage Frequency — Decomposition of Total, Direct, and Indirect Effects

	Effect Value	Boot SE	Boot CI (Lower)	Boot CI (Upper)	Relative Effect (%)
Total Effect	-0.162	0.022	-0.215	-0.109	—
Direct Effect	-0.12	0.041	-0.206	-0.034	74.1%
Indirect Effect	-0.042	0.018	-0.083	-0.01	25.9%

4.8 Conclusion

This study explored the effects of AI Education Experience, Usage Frequency, and Learning Attitude on AI Literacy, with Learning Engagement as a mediating factor. Data reliability and validity were confirmed through a pilot test, with high internal consistency, good sampling adequacy, and significant correlations among variables. Descriptive results showed that participants generally held positive views toward AI learning, while correlation analysis indicated that AI Education Experience, Learning

Attitude, and Learning Engagement were positively related to AI Literacy, and Usage Frequency showed a moderate negative relationship.

Regression analysis revealed that the three predictors explained 63.7% of the variance in AI Literacy, with AI Education Experience and Learning Attitude exerting significant positive effects, and Usage Frequency having a significant negative effect. Mediation tests confirmed that Learning Engagement partially mediated the effects of AI Education Experience and Learning Attitude, contributing about one-quarter of their total influence. In sum, AI Education Experience and Learning Attitude enhance AI Literacy, frequent AI tool use may hinder it, and Learning Engagement plays a crucial role in strengthening these positive effects.

5 DISCUSSION OF FINDINGS

The data for this study came from 330 students from Hebei Normal University in Shijiazhuang, Hebei Province, including undergraduates, masters and doctoral students, covering multiple disciplines such as education and computer science. **AI Education Experience** (3.044), **Usage Frequency** (3.076), **Learning Attitude** (3.048), **Learning Engagement** (3.070), **AI Literacy** (3.040), the backgrounds of these respondents provide various perspectives for the study. The results show that AI Education Experience and Learning Attitude have a significant positive impact on AI Literacy, and there is a negative relationship between Usage Frequency and AI Literacy. Relying on the frequent use of AI tools, but lacking effective learning guidance and educational support, may limit the improvement of students' AI literacy. Learning Engagement has a significant mediating role between Learning Attitude and AI Literacy, and between AI Education Experience and AI Literacy.

5.1 Hypothesis 1

The first hypothesis proposed in this study is that "students who have received AI-related education or training have higher AI literacy". The Pearson correlation coefficient r is 0.645**, indicating a significant positive correlation. Students who have received more comprehensive AI-related education are more likely to have high AI literacy. Students who have received AI education have a deeper understanding of the concept of AI, confirming that AI education experience is a key factor in shaping students' AI literacy, especially for students in technical fields such as computer science. AI experience plays an important role in cultivating technical capabilities (Huang, 2021), providing empirical evidence between AI education experience and AI literacy.

Unlike the impact of AI education in previous studies, this study shows that there is a close positive correlation between the two. The results emphasize the importance of integrating AI education into various academic courses and suggest that AI literacy should be a focus of higher education. Future research can further explore the impact of such education on other capabilities in the field of AI.

5.2 Hypotheses 2

The second hypothesis proposed in this study is that "learning attitude has a positive impact on AI literacy". The Pearson correlation coefficient r is 0.691. shows that there is a significant positive correlation between learning attitude and AI literacy. This indicates that students with positive attitudes have higher AI literacy. The results show that positive learning attitudes are an important predictor of students' ability to understand and effectively apply AI concepts.

The importance of student motivation and mindset for achieving better learning outcomes. Students with positive learning attitudes are generally more engaged and proactive in acquiring knowledge. Motivated learners are more likely to persist in learning and successfully master complex subjects such as AI (Chiu *et al*., 2024).

Although AI education is important, through constructivist theory, students' learning attitudes as motivation play a key role in mastering AI skills. This study provides empirical evidence for the relationship between learning attitudes and AI literacy and should focus on cultivating positive learning attitudes to improve students' AI learning outcomes.

5.3 Hypotheses 3

The third hypothesis posits that "The more positive the students' attitude towards AI, the stronger their AI literacy ability." A moderate negative correlation of r = -0.461 is observed between the frequency of use and AI literacy. This suggests that, although frequent use of AI tools might theoretically enhance AI literacy, excessive use appears to adversely affect students' overall understanding of AI in this study. The negative correlation indicates that if students use AI tools frequently without employing critical thinking to assess whether the AI content is accurate or suitable for their learning, their AI literacy may decrease.

Previous studies typically report a positive correlation between the use of tools and literacy outcomes (Saddhono *et al*., 2024). However, similar research indicates that many students, after frequent use of AI tools, are less willing to engage in deep thinking and tend to over-rely on AI without fully understanding it (Abuzar, 2025). Students who frequently use AI tools may focus more on the technology itself without thoroughly understanding the underlying theories of AI. This explains the negative correlation found in this study.

The idea that high "usage frequency" does not guarantee higher "AI literacy" is underscored. Based on the constructivist theory in this study, it is emphasized that a more balanced approach is needed, combining frequent use of AI tools with professional education. AI literacy requires active construction by students rather than relying solely on experience from usage frequency. Students should be encouraged to use AI with critical thinking. Future research could explore the integration of AI tools with educational participation to enhance "AI literacy," offering suggestions for both educators and students on how to use AI effectively.

5.4 Hypotheses 4

The fourth hypothesis proposed that Learning Engagement partially mediates the relationships between AI Education Experience, Usage Frequency, Learning Attitude, and AI Literacy. The correlation analysis revealed strong positive links between Learning Engagement and AI Literacy (r = 0.706), as well as with Learning Attitude (r = 0.888) and AI Education Experience ($r = 0.432$), and a negative link with Usage Frequency ($r = -0.581$).

Regression and Bootstrap analyses confirmed the mediating role. For AI Education Experience, the direct effect on AI Literacy decreased from 0.805 to 0.563 after including Learning Engagement, while the indirect effect via Learning Engagement accounted for 30.1% of the total impact. For Learning Attitude, the direct effect dropped from 0.818 to 0.650, with 20.5% of the influence mediated through Learning Engagement. In the case of Usage Frequency, the direct effect changed from -0.162 to -0.120, with an indirect effect of -0.042 (25.9%). All confidence intervals excluded zero, confirming significance.

These findings suggest that students' active engagement in AI-related learning enhances the benefits of education and positive attitudes, while also moderating the negative influence of excessive AI tool use. Strengthening Learning Engagement—through interactive activities, guided practice, and reflective learning—can therefore be an effective pathway to improving AI Literacy.

6 CONCLUSION

This study explored the relationships between AI Education Experience, Usage Frequency, Learning Attitude, Learning Engagement, and AI Literacy among university students in China. Using data from 330 respondents across various academic levels and disciplines, the research confirmed that AI Education Experience and Learning Attitude have significant positive impacts on AI Literacy, while Usage Frequency shows a significant negative correlation. Learning Engagement emerged as an important mediator between AI Education Experience and AI Literacy, and between Learning Attitude and AI Literacy, accounting for 20–30% of the total effect in both cases. These results highlight that both formal AI education and students' learning mindset are crucial in cultivating AI literacy, whereas excessive reliance on AI tools without proper guidance may hinder deep learning.

The findings further validate the applicability of constructivist theory in the context of AI education, underscoring that active engagement and positive learning attitudes are as important as technical exposure. While previous research often emphasized technological access and usage, this study demonstrates that the quality of AI learning experiences and the learner's proactive involvement play a greater role in literacy development. The negative effect of high usage frequency suggests that without structured educational support, frequent interaction with AI tools may lead to over-reliance, superficial understanding, and reduced critical thinking skills.

Based on these insights, the study recommends that universities integrate AI education into diverse curricula, adopt teaching strategies that foster active learning and critical thinking, and guide students in the effective use of AI tools. Educators should design activities that enhance Learning Engagement, ensuring that AI literacy is built through meaningful, guided practice rather than passive tool usage. This research contributes empirical evidence to the growing field of AI education and literacy but also acknowledges limitations such as the single-institution sample and reliance on self-reported data. Future research should expand to multi-institutional and longitudinal studies to strengthen generalizability and examine the evolving role of AI in higher education.

REFERENCES

Ahmed, K.; Ali, S.; Habib, M. A.; Khaleel, B.; Khan, N. A.; Ashraf, R. S. Pragmatic perception of politeness in disagreement by Pakistani ESL learners. *Pakistan Journal of Life and Social Science*, v. 22, n. 2, p. 10889–10913, 2024. DOI: 10.57239/PJLSS-2024-22.2.00822

Ahmed, Z.; Ahmed, K.; *et al*. Manipulation of Pakistani women through skin-whitening advertising discourse. In: *PROCEEDINGS OF THE 2019 3RD INTERNATIONAL CONFERENCE OF MANAGEMENT ENGINEERING, SOFTWARE ENGINEERING AND SERVICE SCIENCES*. New York: ACM, 2019. p. 107–111. DOI: 10.1145/3312662.3312705

Ahmed, Z.; Su, L.; Ahmed, K. Pakistani youth manipulated through night-packages advertising discourse. *Human Systems Management*, v. 36, n. 2, p. 151–162, 2017. DOI: 10.3233/HSM-171762

Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes*, *50*(2), 179–211.

Bhatt, P., & Muduli, A. (2024). AI learning intention, learning engagement and behavioral outcomes: An empirical study. Journal of Management Development, 43(6), 920–938. https://doi.org/10.1108/JMD-11-2023-0403

Carolus, A., Koch, M. J., Straka, S., Latoschik, M. E., & Wienrich, C. (2023). MAILS–Meta AI literacy scale: Development and testing of an AI literacy questionnaire based on well-founded competency models and psychological change- and meta-competencies. Computers in Human Behavior: Artificial Humans, 1(2), 100014. https://doi.org/10.1016/j.chbah.2023.100014

Chen, M., Yang, Y., Yang, Q., Chen, J., & Chen, W. (2025). Intelligent agents empowering higher education transformation: Paradigm reconstruction based on DeepSeekR1 and practical exploration of "Zheda Xiansheng". *Modern Educational Technology, 35*(5).

Chen, Y., Wang, S., & Sun, Z. (2023). Effects of higher education institutes' artificial intelligence capability on students' self-efficacy, creativity and learning performance. *Education and Information Technologies, 28*(5), 4919–4939.

Crompton, H., & Burke, D. (2023). Artificial intelligence literacy in higher education. TechTrends, 67(5), 870–882. https://doi.org/10.1007/s11528-023-00829-8

Economides, A. A., & Perifanou, M. (2024, June). University students using ChatGPT in project-based learning. In *Workshop on Digital Transformation in Higher Education* (pp. 27–39). Cham: Springer Nature Switzerland.

Karagiannidis, C., Karamatsouki, A., & Chorozidis, G. (2023). Report on smart education in Greece. In *Smart Education in China and Central & Eastern European Countries* (pp. 131–154). Singapore: Springer Nature Singapore.

Khaleel, B.; Nordin, U. K. U. M.; Ahmed, K.; Anjum, E. Societal stigmatization and support mechanism for rape victims: an analysis of linguistic features of rape judgments in Pakistan. *Pakistan Journal of Life and Social Science*, v. 22, n. 2, p. 980–994, 2024. DOI: 10.57239/PJLSS-2024-22.2.0069

Kong, S. C., Wong, T. L., & Lam, C. C. (2023). Developing artificial intelligence literacy in K-12 education for informed citizenship: A framework and instructional design. Computers and Education: Artificial Intelligence, 4, 100123. https://doi.org/10.1016/j.caeai.2023.100123

Long, D., & Magerko, B. (2020). What is AI literacy? Competencies and design considerations. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems* (pp. 1–16). ACM.

Malik, S. Qin, H. Said, M.K. Ahmed, K. (2020). Quantitative Analysis of the Foreign Language Anxiety: Chinese and Pakistani Postgraduates in Focus. *The Arab World English Journal (AWEJ)*, 11(1.23), 315-330. https://dx.doi.org/10.24093/awej/vol11no1.23

Miao, F., Holmes, W., Huang, R., & Zhang, H. (2021). *AI and education: A guidance for policymakers*. Paris: UNESCO Publishing.

Mohd Amin, M. R., Ismail, I., & Sivakumaran, V. M. (2025). Revolutionizing Education with Artificial Intelligence (AI)? Challenges, and Implications for Open and Distance Learning (ODL). *Social Sciences and Humanities Open*, *11*, 101308.DOI:10.1016/j.ssaho.2025.101308

Ng, D. T. K., Leung, J. K. L., Chu, S. K. W., & Qiao, M. S. (2021). Conceptualizing AI literacy: An exploratory review. *Computers and Education: Artificial Intelligence, 2*, 100041.

Nong, Y., Cui, J., He, Y., Zhang, P., & Zhang, T. (2024). Development and validation of an AI literacy scale. *Journal of Artificial Intelligence Research, 1*(1), 17–26.

Nong, Y., Wu, Z., & Ye, Z. (2024). Enhancing university students' AI literacy: A mixed-method study on curriculum integration. Education and Information Technologies, 29(2), 1123–1142. https://doi.org/10.1007/s10639-023-11857-6

Piaget, J. (1977). *The development of thought: Equilibration of cognitive structures*. New York: Viking Press.

Qin, F., Li, K., & Yan, J. (2020). Understanding user trust in artificial intelligence-based educational systems: Evidence from China. *British Journal of Educational Technology, 51*(5), 1693–1710.

Teixeira, A. I., Martins, S., Lima, S., Pinto, F., Morgado, T., & Valentim, O. (2025, March). A mixed methods approach to understanding mental health literacy among university health students. In *Healthcare* (Vol. 13, No. 7, p. 724). MDPI.

Vygotsky, L. S. (1978). *Mind in society: The development of higher psychological processes*. Cambridge, MA: Harvard University Press.

Wang, K., Cui, W., & Yuan, X. (2025). Artificial intelligence in higher education: The impact of need satisfaction on artificial intelligence literacy mediated by self-regulated learning strategies. *Behavioral Sciences, 15*(2), 165.

Wang, Y., Li, X., & Huang, J. (2025). Promoting AI literacy in higher education: Curriculum design and student engagement strategies. Journal of Educational Technology Development and Exchange, 18(1), 45–62. https://doi.org/10.18785/jetde.1801.03

Wu, D., Sun, X., Liang, S., Qiu, C., & Wei, Z. (2025). Construction of AI literacy evaluation system for college students and an empirical study at Wuhan University. *Frontiers of Digital Education, 2*(1), 6.

Wu, T. M., Chan, E. A. H., Wong, H. S. M., & Chan, J. K. (2025). Perceived artificial intelligence literacy and employability of university students. Education+ Training, 67(2), 258–274. https://doi.org/10.1108/ET-07-2023-0212

Wut, T. M., Chan, E. A. H., Wong, H. S. M., & Chan, J. K. (2025). Perceived artificial intelligence literacy and employability of university students. Education+ Training, 67(2), 258–274. https://doi.org/10.1108/ET-07-2023-0212

Yang, Q. F., Lian, L. W., & Zhao, J. H. (2023). Developing a gamified artificial intelligence educational robot to promote learning effectiveness and behavior in laboratory safety courses for undergraduate students. *International Journal of Educational Technology in Higher Education, 20*(1), 18.