Journal of International Education and Development
2025, VOL. 9, NO. 10, 298-303
DOI: 10.47297/wspiedWSP2516-250068.20250910

The Influence of Attitudes Toward Artificial Intelligence Use on University Students' Learning Motivation

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ABSTRACT

This paper explores how undergraduates' attitudes towards artificial intelligence (AI) affect their motivation to learn, and focuses on the moderating role of disciplinary background. Under the background of the national promotion of the integration of artificial intelligence and education, and in response to the status quo that existing studies pay less attention to students' subjective attitudes and disciplinary differences, this study conducted a questionnaire survey on 306 undergraduates in colleges and universities. Correlation and regression analyses revealed that a positive attitude toward AI use significantly and positively predicts both intrinsic and extrinsic motivation. Furthermore, disciplinary background moderates this relationship, with the effect being significantly stronger among students in natural science disciplines than those in humanities and social sciences. The results suggest that the promotion and use of AI should be differentiated according to the characteristics of disciplines in order to stimulate students' learning motivation more effectively. This study also provides empirical evidence to clarify the misconception that AI has a negative impact on learning, and emphasises that its effect depends on the specific context of use and the attributes of the discipline.

KEYWORDS

Learning motivation; Disciplinary moderating role; University students

1 Introduction

1.1 Background to the study

Since 2021, China has upgraded the development of artificial intelligence to a national strategy, and the integration of "artificial intelligence + education" has gradually become the inevitable norm [1]. Motivation is a critical factor influencing students' academic achievement and satisfaction, serving as an internal drive that directly facilitates college students' learning activities. With the ongoing advancement of generative artificial intelligence, students are increasingly using AI in their learning processes. Therefore, exploring the impact of AI on learning motivation carries significant theoretical and practical importance.

1.2 Overview of research

1.2.1 Overview of domestic and international research

Several studies suggest that AI has the potential to enhance learning motivation in educational contexts [2-3]. (Mu Ping, 2019; Yan et al., 2017) In particular, research on the use of Generative Artificial Intelligence (GenAI) in personalised vocabulary learning has shown that the technology helps to enhance students' intrinsic motivation to learn [4]. (Huang J, 2024)

Meanwhile several studies have justified the motivation of AI to stimulate learning through case models, examples, etc., and its ability to provide a positive impact on learning [5-7]. (Li Lu, 2021; Chen Yang, 2024; Rosdiana Im, 2025). Artificial Intelligence can take on 12 auxiliary roles such as teaching assistant and analyst, releasing teachers' energy to focus on students' higher-order ability development [8] (Yu Shengquan,2018)

There is also a small amount of current research on differences in the impact of AI across disciplines. It is noted that the attitudes and results of the use of artificial intelligence differ among students of different disciplines [9].(Arslanova K Z, 2024) The phenomenon may be related to the sensitivity to emerging technologies fostered by their scientific and technological educational backgrounds, and related research in psychology and education further suggests that science and engineering students usually have strong analytical and technological application skills, which makes it easier for them to comprehend and use AI tools. [1] (Junling Kan, 2025)

1.2.2 Literature review

Current research on AI and learning motivation in China shows a tendency of "technocentrism", with a large number of results focusing on the implementation of AI tools and short-term learning effect verification, but neglecting a key variable - students' own attitude and stance towards AI. A large number of results focus on the implementation of AI tools and the verification of short-term learning effects, but neglect a key variable - students' own attitudes towards AI. Future research will be devoted to deepening the application of AI technology in mental health education and systematically evaluating the effectiveness of different interventions and cultivation strategies [10]. Meanwhile, while educators are keen on designing more accurate algorithmic push, liberal arts students may turn off smart assistants due to ethical concerns, while science students cheer for efficiency improvement. Different disciplinary backgrounds are likely to bring about different attitudes towards the use of AI, leading to differences in college students' motivation to learn. Although there have been studies on the impact of differences in disciplines at home and abroad, there is a lack of in-depth exploration of how different disciplinary backgrounds shape the differences in attitudes towards the use of AI in the context of students' subjective attitudes.

1.3 Research hypotheses and objectives

Since most domestic and international research studies focus on the effects of AI tools themselves, little attention has been paid to students' own attitudinal stance towards AI and the differences brought about by their disciplinary backgrounds.

Therefore, this study aims to investigate how university students' attitudes towards the use of AI affect their motivation to learn. The study examines whether there are differences between different disciplinary backgrounds regarding the influence of attitudes towards AI usage on learning motivation. Suggestions are made for different groups of students to stimulate and maintain their motivation through the use of AI technology, and to break through the current dilemma of "one-size-fits-all" implementation of AI education.

2 Participants and materials

A convenience sample of about 300 undergraduate college students who have used or are continuing to use AIGC applications is expected to be taken.

The questionnaire used in this study was a combination of the following scales, with the addition of the option of "type of speciality" (science and technology/humanities and social sciences).

The scale of "Research on the factors influencing the continuous use of AIGC by university students" was adopted. The scale of "Research on factors influencing the continuous use of AIGC by university students" was revised by Yang Tranquillity (2024), which consisted of 24 items with a 5-point scale, and the Cronbach's alpha values were 0.859, 0.778, 0.863, and 0.796, respectively.

Learning Motivation Scale. The scale was developed by Zhang Lei of Beijing Normal University on the basis of Pianta's (1994) questionnaire. The scale consists of four dimensions and 22 questions. The questionnaire ranges from "not at all" to "completely" and is based on a 5-point scale. The internal consistency of the scale was 0.83, the split-half reliability was 0.82, and the re-test reliability was 0.80. The scale has been used to assess the reliability of the survey.

3 Result

3.1 Descriptive analyses

3.1.1 Demographic information statistics

In Table 1, this study used questionnaires to collect data, through the distribution of questionnaires, the questionnaires will be recovered, data cleaning, excluding invalid samples, to get a valid sample of 306, the valid samples obtained can support the experimental research. The basic demographic information of the pre-survey is organised as follows:

The total number of valid samples in this study is 306. In terms of subject categories, there were 124 students in the humanities and social sciences, accounting for 40.52 per cent, and 182 students in the natural sciences, accounting for

Table 1

Frequency analysis results

name (of a thing)	options (as in computer software settings)	Frequency	Percentage (%)	Cumulative percentage (%)
distinguishing between the sexes	male	147	48.04	48.04
	female	159	51.96	100.00
grade	first-year university student	13	4.25	4.25
	second-year university student	110	35.95	40.20
	third-year university student	105	34.31	74.51
	fourth-year university student	78	25.49	100.00
How often do you use AIGC apps each month?	More than 25	72	23.53	23.53
	16-25 times	44	14.38	37.91
	5-15 times	106	34.64	72.55
	Less than 5	84	27.45	100.00
subject category	Humanities and Social Sciences category	124	40.52	40.52
	Natural science disciplines	182	59.48	100.00
add up the total		306	100.0	100.0

59.48 per cent, indicating a balanced structure of this sample.

3.1.2 Statistics on scores for each dimension

Table 2

descriptive statistics									
	N	minimum value	maximum values	average value	(statistics) standard deviation	skewness		kurtosis	
						statisticians	standard error	statisticians	standard error
attitude	306	1.71	6.06	3.82	1.13	0.079	0.139	-1.308	0.278
endogenous	306	1.33	5.42	3.40	0.95	-0.154	0.139	-1.048	0.278
exogenous	306	1.50	5.08	3.24	0.95	-0.006	0.139	-1.151	0.278
Effective number of cases (columns)	306								

Table 2 shows the descriptive statistics analysed for the three variables of attitude towards use, intrinsic motivation and extrinsic motivation, with the mean values of each variable ranging from 3.2 to 3.8, which is consistent with a normal distribution.

3.1.3 Multiple Responses (AIGC-type applications you are using or have used)

Analysed from the perspective of popularity, text generation tools had the highest usage rate, with 84.31 per cent of respondents indicating that they had used such tools; image generation tools had a usage rate of 56.21 per cent; video generation tools had a usage rate of 35.62 per cent; audio generation tools had a usage rate of 21.90 per cent; design tools had a usage rate of 17.32 per cent; and other types of tools had a usage rate of 9.80 per cent.

The data show that text generation and image generation tools have a high degree of popularity in the current sample and are the two most widely used categories of AIGC applications. Video generation, audio generation and design tools have relatively low usage rates, showing that there is a significant difference in the degree of adoption of different categories of AIGC applications. Overall, the respondents showed a high willingness to try and use multiple types of AIGC applications.

3.2 Reliability analysis

This questionnaire has good structural validity with the values of Kronbach's alpha coefficient >0.9 and KMO=0.939 for all latitudes. The data collected by this questionnaire are informative and can be used for empirical analyses.

3.3 Correlation analysis

Pearson correlation analyses were conducted to examine the correlations among the three variables of attitude toward use, intrinsic motivation and extrinsic motivation. The results of the analyses showed that there were significant correlations between the variables, as follows:

There is a significant positive correlation between attitude towards use and intrinsic motivation, with a correlation coefficient of 0.233 and a significance level of 0.01. There is also a significant positive correlation between attitude towards use and extrinsic motivation, with a correlation coefficient of 0.253 and a significance level of 0.01.

The correlation coefficient between intrinsic and extrinsic motivation for learning is 0.064, and the significance level is 0.265, which does not meet the criterion of statistical significance.

In terms of the magnitude of correlation coefficients, the correlation between attitudes towards use and extrinsic motivation is slightly higher than that between attitudes towards use and intrinsic motivation, but both of them are in the range of low positive correlation. All analyses were based on 306 valid cases to ensure the reliability of the results.

Attitude toward use was significantly positively correlated with both types of motivation, while intrinsic and extrinsic motivation were relatively independent, a finding that provides an important basis for understanding the psychological mechanisms underlying users' adoption of AIGC technology.

3.4 Regression analysis

Stratified regression analyses were conducted to examine the predictive effects of attitudes toward AI use on the dependent variables intrinsic motivation to learn and extrinsic motivation to learn in the overall sample, the humanities and social sciences disciplines sub-sample, and the natural sciences disciplines sub-sample, respectively.

In Table 3, the dependent variable is intrinsic motivation to learn. In the overall sample analysis, the regression model reached the level of statistical significance with an F-value of 17.501, a p-value of less than 0.01, and an adjusted R-square of 0.051, indicating that attitudes toward use explained 5.1% of the variance in the dependent variable. The regression coefficient of use attitude is 0.196, standard error is 0.047, standardised coefficient β is 0.233, t-value is 4.183, p-value is less than 0.01, which indicates that the use attitude has a significant positive predictive effect on the dependent variable intrinsic motivation to learn.

In Table 4, the dependent variable is extrinsic motivation to learn. In the overall sample, the regression model is

Table 3

Dependent variable: intrinsic motivation															
Subgroup regression modelling (n=306)															
	synthesis					Humanities and Social Sciences category					Natural science disciplines				
	B	Standard Error	t	p	β	B	Standard Error	t	p	β	B	Standard Error	t	p	β
a constant (math.)	2.646**	0.187	14.168	0.000	-	2.762**	0.304	9.096	0.000	-	2.569**	0.238	10.798	0.000	-
attitude	0.196**	0.047	4.183	0.000	0.233	0.158*	0.075	2.100	0.038	0.187	0.223**	0.060	3.692	0.000	0.265
sample size	306					124					182				
R 2	0.054					0.035					0.070				
Adjustment R 2	0.051					0.027					0.065				
F Value	F (1,304)=17.501,p=0.000					F (1,122)=4.410,p=0.038					F (1,180)=13.630,p=0.000				
* p<0.05 ** p<0.01															

Table 4

Dependent variable: extrinsic motivation to learn															
Subgroup regression modelling (n=306)															
	synthesis					Humanities and Social Sciences category					Natural science disciplines				
	B	Standard Error	t	p	β	B	Standard Error	t	p	β	B	Standard Error	t	p	β
a constant (math.)	2.430**	0.186	13.085	0.000	-	2.466**	0.305	8.092	0.000	-	2.392**	0.234	10.243	0.000	-
attitude	0.213**	0.047	4.561	0.000	0.253	0.177*	0.075	2.350	0.020	0.208	0.241**	0.059	4.072	0.000	0.290
sample size	306					124					182				
R 2	0.064					0.043					0.084				
Adjustment R 2	0.061					0.035					0.079				
F Value	F (1,304)=20.805,p=0.000					F (1,122)=5.522,p=0.020					F (1,180)=16.583,p=0.000				
* p<0.05 ** p<0.01															

significant with an F value of 20.805, p value less than 0.01, and adjusted R-square of 0.061. The unstandardised regression coefficient of attitude towards use is 0.213, standard error 0.047, standardised coefficient of β is 0.253, and the t value is 4.561, p value is less than 0.01. The results show that the attitude towards use has a significant and positive predictive effect on the dependent variable, explaining 6.1% of the variance of the dependent variable. It can explain 6.1% of the variance of the dependent variable.

According to Tables 3 and 4, in the sub-sample of humanities and social disciplines group, when the dependent variable is intrinsic motivation to learn, the regression model also reaches the level of significance, with the F value of 4.410, p value equal to 0.038, and adjusted R-square of 0.027. The regression coefficient of the attitude to use is 0.158, standard error 0.075, standardised coefficient of β is 0.187, and the t value is 2.100, and p value equal to 0.038, indicating that attitude toward use still has a significant positive predictive effect on the dependent variable in this subject group, but the explanatory strength is relatively weak. When the dependent variable is extrinsic motivation, the regression model is significant, with F value of 5.522, p value equal to 0.020, and adjusted R-square of 0.035. The unstandardised regression coefficient of attitude towards use is 0.177, standard error is 0.075, standardised coefficient β is 0.208, t value is 2.350, and p value is equal to 0.020, which suggests that attitude towards use still has a significant positive predictive effect on the dependent variable in this discipline group, but the explanatory power is relatively weak. attitude still has a significant positive predictive effect on the dependent variable, but the explanatory strength is also relatively weak.

In the sub-sample of the natural science discipline group, when the dependent variable is intrinsic motivation to learn, the regression model shows stronger predictive power with an F-value of 13.630, p-value less than 0.01 and adjusted R-square of 0.065. The regression coefficient of attitude towards use is 0.223, standard error is 0.060, standardised coefficient β is 0.265 and t-value is 3.692, p-value less than 0.01, which indicates that attitude towards use has a significant and stronger positive predictive effect on the dependent variable intrinsic learning motivation in this subject group. When the dependent variable is extrinsic motivation, the regression model also shows stronger predictive power, with an F value of 16.583, p value less than 0.01, and an adjusted R-square of 0.079. The unstandardised regression coefficient of attitude towards use is 0.241, standard error is 0.059, standardised coefficient β is 0.290, and t value is 4.072, p value is less than 0.01. The results show that attitude towards use has a significant and stronger positive predictive effect on intrinsic motivation in this subject group. The results show that in this discipline, attitude towards use has a significant and stronger positive predictive effect on the dependent variable, and can explain 7.9% of the variance of the dependent variable.

By comparing the regression coefficients of different subject groups, it was found that the standardised regression coefficient of students in the natural science subject group was 0.265, higher than that of students in the humanities and social sciences subject group (0.187) when the dependent variable was intrinsic motivation for learning, and the standardised regression coefficient of students in the natural science subject group was 0.290, higher than that of students in the humanities and social sciences subject group (0.208) when the dependent variable was extrinsic motivation for learning, which indicates that the use of attitude is more effective in predicting the students of natural science disciplines. The constant terms of the three models reached the level of statistical significance, and the overall model fit was good.

Attitude towards use has a significant positive predictive effect on the dependent variable, and this predictive effect differs significantly among different disciplinary groups. The strength of prediction was significantly higher for students of natural sciences than for students of humanities and social sciences, suggesting that disciplinary background plays a moderating role in the relationship between attitudes toward use and the dependent variables of intrinsic and extrinsic motivation.

4 Discussion

4.1 Discussion of results

The results indicate that a positive attitude toward AI use is associated with higher levels of both intrinsic and extrinsic motivation. Notably, intrinsic and extrinsic motivation were not significantly correlated, suggesting they represent distinct motivational pathways. Therefore, cultivating and shaping students' positive cognition and attitude towards AI is conducive to stimulating their intrinsic interest and external drive to use AI for learning.

Notably, the correlation between intrinsic and extrinsic motivation was not statistically significant, which indicates that they are relatively independent. Therefore, when promoting AI, we can start from two different paths: stimulating users' intrinsic interest and providing external motivation, which are not in conflict with each other.

Subgroup regression showed that disciplinary background played an important moderating role in the relationship between attitudes toward AI use and motivation. College students' attitudes toward AI use predicted both intrinsic and extrinsic motivation much more strongly in the natural sciences than in the humanities and social sciences.

A plausible explanation for this phenomenon lies in the differences in problem-solving paradigms across disciplines. For students of the natural sciences, the use of AI can be directly embedded in their learning, e.g., for processing data, debugging code, visualising results, formulating hypotheses, and so on. The efficiency gains and performance gains are more immediately visible. Therefore, positive attitudes towards AI use can be directly and efficiently translated into stronger motivation, not only intrinsic motivation for self-interest, but also extrinsic motivation for completing tasks faster and more efficiently. On the contrary, humanities and social sciences disciplines pay more attention to critical thinking, emotional expression and value judgement, while the current mainstream AI tools can generate text and images, but the text generated by them is usually regarded as lacking in academic depth and criticality. Therefore, students of humanities and social sciences may need to spend a lot of effort to verify, revise and deepen the generated content. This "high modification cost" and "uncertainty" undermines the efficiency of transforming positive usage attitudes into learning motivation. At the same time, AI applications may raise deeper concerns about originality, academic integrity and ethics, resulting in a relatively cautious and weak transition from positive attitudes to motivation. Therefore, although students' attitudes towards AI use are positive, the tools are not perfectly suited to the required academic tasks, resulting in relatively weak motivation enhancement.

Therefore, this study breaks through the limitation of homogenisation of user attitudes in previous studies, and not only confirms the positive impact of AI attitudes on learning motivation, but also reveals the key role of moderation in different subject backgrounds. This study suggests that educators and technology developers should abandon the "one-size-fits-all" strategy and focus on the differentiation of subject matter and user needs. At the same time, the results of this study provide empirical evidence to clarify the misconceptions about the impact of AI on learning among the general public and the education sector. Positive attitudes towards the use of technology are significantly associated with increased motivation to learn, but do not necessarily lead to dependence or inertia; the nature of the impact is highly dependent on the subject matter context and the mode of use. This helps to guide society to take a more dialectical and open view of the educational role of AI, and to avoid hindering the development of AI teaching and learning due to excessive concerns about negative effects.

4.2 Recommendations

In promoting the use of AI applications, attention should be paid to the diversity of student groups. For students of natural science disciplines, we can focus on its instrumental value in enhancing the efficiency of learning and research, while for students of humanities and social sciences disciplines, we can focus on its empowering value in stimulating inspiration, assisting creative expression and expanding thinking.

At the school level, since positive attitudes towards use are key to driving student motivation, schools and organisations can positively guide students to understand the appropriate amount and correct use of AI to motivate learning.

In terms of AI product development, application developers can consider developing more targeted functional modules to meet the specific needs of students in different disciplines, so as to enhance the experience of all types of users.

4.3 Research limitations

There are still some limitations in this study. Firstly, the sample is mainly from undergraduate students in colleges and universities, and the generalisability of the conclusions needs to be further verified in other groups. Second, this study did not analyse the specific latitude of "attitude towards usage" in detail, which is rather general. Thirdly, future research can introduce more variables, such as personal innovativeness, social influence, usage scenarios, etc., to construct a more comprehensive model to investigate the influence of AI usage attitude on learning motivation.

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