Education Science and Management
https://www.acadlore.com/journals/ESM

The Impact of ChatGPT on Learning Motivation: A Study Based on Self-Determination Theory

Lian Zhou[1*], Junjun Li[2]

[1] New Energy Photovoltaic Industry Research Center, Qinghai University, 810016 Xining, China
[2] International College, National Institute of Development Administration, 10240 Bangkok, Thailand

[*] Correspondence: Lian Zhou (zhoulianminai@126.com)

Received: 03-20-2023 **Revised:** 04-21-2023 **Accepted:** 05-05-2023

Citation: Zhou, L. & Li, J. J. (2023). The impact of ChatGPT on learning motivation: A study based on self-determination theory. *Educ. Sci. Manag., 1*(1), 19-29. https://doi.org/10.56578/esm010103.

Abstract: This study aimed to investigate the impact of using ChatGPT as an auxiliary learning tool on university students' learning motivation. Structural equation modeling and regression analysis were employed as the data analysis methods. Questionnaire surveys were conducted to collect data on 196 university students. The results indicated that after using ChatGPT, a negative correlation was found between tension-pressure and interest-enjoyment. Perceived competence was significantly positively correlated with interest-enjoyment, while the correlation between perceived value and interest-enjoyment was insignificant. These three variables were found to have varying degrees of influence on interest-enjoyment in the regression analysis. The study concluded that ChatGPT had a certain impact on learning motivation, but university students' frequency of use and proficiency was relatively low, requiring further training. The significance of this study lies in providing a new pedagogical approach that enables students to keep up with contemporary trends. The findings of this study have substantial theoretical and practical implications, offering novel perspectives and avenues for research on university students' learning motivation and contributing to educational reforms by providing valuable insights and directions.

Keywords: ChatGPT; Education management; Learning motivation; Self-determination theory; Artificial intelligence

1. Introduction

In the contemporary information age, the swift advancement of artificial intelligence technology offers new opportunities and challenges for the education sector. ChatGPT, an advanced natural language processing technology, has the potential to provide personalized learning support and teaching services to students, thereby enhancing their learning motivation and achievement. This study investigates the impact of ChatGPT on university students' learning motivation and analyzes its theoretical and practical significance.

Learning motivation among university students refers to the internal drive and motivation that students generate, maintain, and regulate their learning behavior during the learning process. It serves as a crucial factor affecting students' learning achievement and academic satisfaction (Gopalan et al., 2017). Self-determination theory posits that humans have three basic psychological needs: autonomy, competence, and relatedness. These psychological needs are essential for individuals' health and well-being and lay the foundation for intrinsic motivation and external incentives, which can promote individuals' learning, behavior, and achievement (Deci & Ryan, 1985).

Autonomy, in particular, refers to individuals' responsibility for their behavior and decisions and their capacity to act in their own way. Competence denotes individuals' ability to effectively process information and solve problems. Relatedness encompasses individuals' need to establish connections and relationships with others to satisfy their social needs. These three psychological needs are interdependent, and the lack of any one of them can have a detrimental impact on individuals' learning motivation and achievement.

As an intelligent learning support and personalized teaching service, ChatGPT is capable of meeting university students' autonomy, competence, and relatedness needs by providing diverse and timely feedback and guidance through intelligent dialogue, developing personalized teaching plans and educational programs, and enhancing learning engagement and experience. For instance, a study discovered that using a chatbot with positive social presence and human similarity effectively improved the learning motivation of Iranian English as a foreign language learner (Ebadi & Amini, 2022). Similar research findings were reported in a study by Chiu et al. (2023), which found that utilizing AI-based chatbots improved students' learning motivation, while teacher support and guidance enhanced students' learning outcomes.

Moreover, ChatGPT technology has the potential to assist students in enhancing learning efficiency and autonomy. For instance, ChatGPT technology can offer personalized learning support and teaching services based on students' learning progress and ability levels, aiding students in better understanding and mastering knowledge. Simultaneously, ChatGPT technology can assist students in identifying their learning problems and difficulties through intelligent dialogue and feedback, thereby improving their self-reflection and problem-solving abilities.

Nevertheless, ChatGPT technology may also manifest some negative effects. For instance, students may become overly reliant on technology, leading to diminished interpersonal communication and social skills. To mitigate these issues, schools and teachers can utilize ChatGPT technology judiciously and strengthen students' cultivation of interpersonal communication and social skills (Mhlanga, 2023).

The theoretical significance of this research lies in providing a personalized learning support program based on ChatGPT technology, capable of meeting students' autonomy, competence, and relatedness needs while improving their learning motivation and achievement. Additionally, this study offers novel ideas and methods for teaching design and practice in the education sector.

In practical terms, ChatGPT technology can be employed to enhance educational outcomes (Zhai & Center, 2023). For instance, schools can utilize ChatGPT technology to develop personalized learning support tools, offer diverse and timely feedback and guidance to students, assist them in better understanding and mastering knowledge, and improve their learning motivation and achievement. Furthermore, teachers can use ChatGPT technology to create personalized learning resources, provide more accurate learning resources and support to students, and enhance their learning motivation and achievement.

In conclusion, ChatGPT, as an intelligent learning support and personalized teaching service, can furnish diverse and timely feedback and guidance to university students, address their autonomy, competence, and relatedness needs, and ameliorate their learning motivation and achievement. This study also explores the potential negative effects of ChatGPT technology and methods to alleviate these problems, as well as how to reasonably employ ChatGPT technology in teaching design and practice to improve educational outcomes. Consequently, ChatGPT technology holds vast prospects for application in the education sector and warrants further research and exploration.

2. Literature Review

2.1 Self-Determination Theory (SDT)

Self-Determination Theory (SDT) is a psychological theory proposed by American psychologists Deci & Ryan (1985) in the 1980s. The theory posits three basic psychological needs: autonomy, competence, and relatedness (Ryan & Deci, 2000). Autonomy refers to self-initiated and selective behavior, competence refers to the feeling of effectively performing tasks with confidence, and relatedness is defined as the emotional support individuals receive or give to others in the interaction process. Subsequently, researchers have further explored and explained these basic needs, refining the internal structure and motivational components of SDT (Ryan & Deci, 2000; Sheldon & Elliot, 1999). It is found that when individuals experience fulfillment in their autonomy, competence, and relatedness, they feel intrinsically motivated and content, rather than being motivated by external rewards or punishments. Consequently, they are more willing to invest in learning, work, and other activities. Therefore, SDT is highly relevant for understanding learning motivation.

2.2 The Relationship Between Self-Determination Theory and Learning Motivation

Within the framework of SDT, learning motivation can be viewed as an intrinsic motivation, where individuals participate in activities for the pleasure and satisfaction derived from the activity itself, rather than external rewards or punishments. In the learning process, autonomy, relatedness, and competence play crucial roles. It has been found that students are more likely to engage in learning activities when they feel autonomous, related, and competent (Gagné & Deci, 2005). Multiple studies have underscored the importance of SDT in understanding learning motivation (Ryan & Deci, 2000). For instance, when students perceive that they have more choices and can make decisions according to their own will, they usually exhibit higher interest and engagement (Vansteenkiste et al., 2012). Supporting students' autonomy, competence, and relatedness can improve their learning motivation and performance (Reeve, 2009), and increase their interest and academic achievement (Krapp, 1999; Ryan & Deci, 2020). In the context of online education, interaction, internet self-efficacy, and self-regulated learning have been identified as critical factors in predicting student satisfaction (Kuo et al., 2014). Moreover, supporting employees' autonomy, competence, and relatedness in the workplace can enhance work motivation, leading to improved performance and satisfaction (Gagné & Deci, 2005).

In this study, the focus is on intrinsic motivation. Based on SDT, the intrinsic motivational factors of university students' learning motivation and their impact on academic performance after learning ChatGPT are explored.

2.3 ChatGPT Profile

ChatGPT is a neural network model based on the transformer architecture that has been pre-trained by OpenAI. It excels in natural language processing tasks, such as text generation, summarization, and dialogue systems. Before the advent of ChatGPT, intelligent chatbots had been widely employed in various fields, particularly in education, and had achieved significant results. For example, some chatbots were found to help students improve their punctuation learning effectiveness and promote open and flexible learning environments (Vázquez-Cano et al., 2021). In addition, chatbots have the potential to provide personalized learning support for students and promote learning interaction (Okonkwo & Ade-Ibijola, 2021).

In comparison with chatbots, ChatGPT does not require responding according to predetermined rules or intentions and exhibits superior automatic conversation capabilities. Applications of ChatGPT in various fields have been reported, such as medical exams (Gilson et al., 2022; Gilson et al., 2023), improving students' academic writing ability (Stokel-Walker, 2022), and insights into educational reforms (Kung et al., 2023; Kasneci et al., 2023).

Despite its advanced technology, ChatGPT has some potential drawbacks. For instance, due to the lack of human emotion and intuition, ChatGPT may not fully comprehend the context and semantics of certain questions, leading to inaccurate or impersonal responses (Mhlanga, 2023). Furthermore, the power of ChatGPT raises ethical, legal, and economic concerns, such as pervasive AI "counterfeiting," plagiarism, and intellectual property infringement (Flanagin et al., 2023; Stokel-Walker, 2022). This necessitates the establishment of robust regulatory frameworks and professional guidelines that safeguard the integrity of academic knowledge production and dissemination in the era of advanced AI technologies (Cotton et al., 2023). At the same time, ensuring data privacy and security, as well as proper ethical and legal guidance, are crucial factors that must be considered (Sallam, 2023).

2.4 The Relationship Between Self-Determination Theory, Learning Motivation, and ChatGPT

The core tenet of self-determination theory is that conditions and environments that support the three innate psychological needs of autonomy, competence, and relatedness can foster individuals' high-quality motivational engagement. When individuals' need for autonomy, competence, and relatedness is met, they are intrinsically motivated to engage in certain behaviors (Ryan & Deci, 2000). Moreover, their motivational state further influences their behavior, emotion, and cognition. In the context of exercise professionals, for example, supporting individuals' autonomy has been identified as a motivational strategy in line with the core principles of SDT (Sánchez-Oliva et al., 2021). Additionally, students' perceived teacher autonomy support and structure have been found to influence their self-regulated learning, motivation, and problem behavior (Vansteenkiste et al., 2012).

Research has demonstrated that good learning motivation can help students be more attentive, autonomous, and proactive in the learning process. In the modern technological environment, students' interaction with learning content can enhance their satisfaction and strengthen their interest and motivation (Heaven, 2020; Kuo et al., 2014). The application of ChatGPT in the education field has the potential to identify students' learning goals and focus, as well as enhance their learning motivation by increasing interaction with them (Mhlanga, 2023; Rudolph et al., 2023; Zhai & Center, 2023). Therefore, the impact of ChatGPT on students' learning motivation warrants further exploration.

Throughout the entire research process, the study subjects were university students who were familiar with and had used ChatGPT. Therefore, prior to conducting the questionnaire survey, a group of students who were easily sampled was trained in the use of ChatGPT and given a certain amount of time to become familiar with the tool. Based on this, it can be hypothesized that when using ChatGPT, it may better meet the three psychological needs of autonomy, relatedness, and competence for university students. The satisfaction of the three psychological needs indicates that the three independent variables Tension-pressure, Perceived Competence, and Perceived Value related to the three psychological needs can significantly affect the dependent variable. The significant effect is to promote Interest-enjoy, which is the expression of learning motivation (Figure 1). Consequently, it is suggested that ChatGPT is a very practical and promising educational tool.

2.5 Theoretical Model

The research model is as Figure 1:

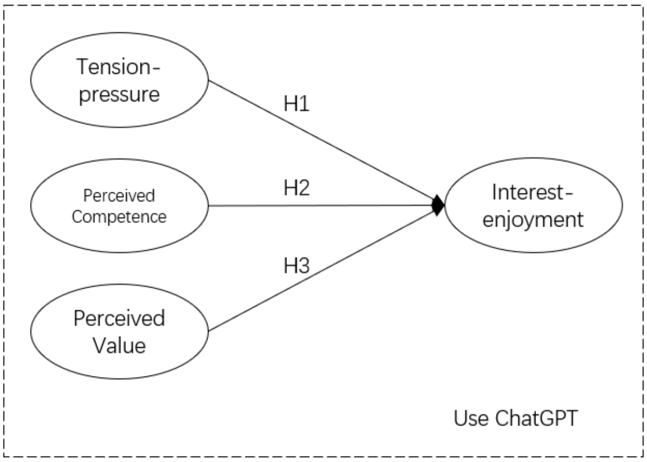

Figure 1. Research model

2.6 Research Hypotheses

H1: After ChatGPT-assisted learning, there is a significant negative correlation between tension-pressure and interests-enjoyment.

H2: After ChatGPT-assisted learning, there is a significant positive correlation between perceived competence and interests-enjoyment.

H3: After ChatGPT-assisted learning, there is a significant positive correlation between perceived value and interests-enjoyment.

3. Methodology

In this study, the primary research method employed is a questionnaire survey aimed at exploring the factors that influence the learning motivation of university students. Before distributing the questionnaire, a comprehensive ChatGPT-related training session is conducted for the participating students to enhance the accuracy of their responses and provide them with sufficient hands-on practice time.

To achieve the research objectives, training materials related to ChatGPT are developed through continuous practice and experiential learning and are presented in written and demonstrative forms. For instance, the training lasts for two hours and includes a combination of presentations, demonstrations, and interactive activities to ensure students fully understand the system. The survey is distributed to students who have either undergone training or have not, with the selection criteria being those who have used ChatGPT. Although the response rate is not very high after screening the questions, it ensures the reliability of the survey results. A total of 269 questionnaires are collected, with 196 valid responses, resulting in an effective rate of 73%. Additionally, thorough revisions and validations of the motivation questionnaire are conducted, incorporating feedback from experts in the field and pilot testing with a smaller sample of students. This process ensures that the questionnaire is both reliable and valid, effectively capturing the factors influencing learning motivation.

Lastly, necessary steps are taken to ensure the representativeness and generalizability of the sample. Participants are recruited from various universities, academic disciplines, and demographic backgrounds, thereby creating a diverse and representative sample. By doing so, the findings of the study have broader applicability, contributing valuable insights into the factors affecting university students' learning motivation.

3.1 Scale Selection

The Motivation Questionnaire is a multidimensional measurement tool adapted from the Intrinsic Motivation Inventory (IMI) by Yin et al. (2021), originally developed by McAuley et al. (1989), to assess participants' subjective experiences related to the target activity in the experiment and measure university students' subjective experiences of intrinsic motivation related to the learning environment. The questionnaire aims to evaluate the degree of individuals' intrinsic motivation when engaging in a certain activity. A total of 29 questions are designed to measure the four independent variables and their relationship with learning motivation, including demographic information questions and research content measurement questions. These questions aim to explore whether factors such as tension-pressure, perceived choice, perceived competence, and perceived value among university students will significantly affect the level of learning motivation (interest-enjoyment) after using ChatGPT to assist learning.

3.2 Research Tool

The study uses the Question Star platform to distribute questionnaires and employs convenience sampling and snowball sampling to obtain data. The questionnaire consists of two parts: the first part is personal basic information, and the second part is research measurement questions, scored using a Likert five-point-scale, with 1 indicating "strongly disagree" and 5 indicating "strongly agree". The research measurement questions are used to measure four independent variables, including interest-enjoyment, tension-pressure, perceived competence, and perceived value.

3.3 Data Analysis Methods

Statistical analysis methods are employed to analyze the data. Firstly, the questionnaire data are cleaned and organized, and the score of each variable is calculated. Then, descriptive statistical methods are used to analyze the basic characteristics of the sample, including sample size, gender ratio, and grade distribution. Next, SPSS 26.0 is used for confirmatory factor analysis and exploratory factor analysis to explore the reliability and validity of the measurement questions. Then, AMOS 24.0 is used to verify the significance and effect of the paths. Finally, the research results are interpreted and discussed, and corresponding suggestions and measures are proposed.

4. Results

4.1 Demographic Variables

Table 1 shows the basic demographic information of this study.

Table 1. Respondents' statistics

Indicators	Category	N.	Percent
Gender	Male	147	75.0%
	Female	49	25.0%
Grade	Freshman	59	30.1%
	Sophomore	51	26.0%
	Junior	40	20.4%
	Senior	44	22.4%
	Graduated	2	1.0%
Spend time per week	Hardly use	35	17.9%
	Below 60 min	126	64.3%
	60-120 min	31	15.8%
	Above 120 min	4	2.0%
Purpose of use	Hobbies and interests	125	63.8%
	Finish homework	101	51.5%
	Class content supplement	86	43.9%
	Research paper writing	65	33.2%
	Employment inquiry	55	28.1%
	Other	55	28.1%

4.2 Reliability Analysis

In accordance with reliability analysis standards, a higher value of Cronbach's α indicates a higher reliability of the questionnaire. Table 2 presents the SPSS reliability analysis results, which reveal that the Cronbach's α reliability coefficients for the four research variables are as follows: Interest-enjoyment (IE) 0.886; Tension-pressure (TP) 0.859; Perceived Choice (PCO) 0.747; Perceived Value (PV) 0.912. Since each variable had at least three measurement questions and removing them had no significant impact on the data, TP1 was retained. The values of each variable were greater than or equal to 0.7, indicating that the reliability analysis met the standards, and the data were accurate and dependable. Consequently, the research sample accurately reflected the problem. Moreover, after deletion, the Cronbach's α coefficient of each item was lower than the Cronbach's α coefficient of the variable, suggesting that no item required correction. In conclusion, the scale's reliability satisfies the requirements for reliable quality.

Table 2. Analysis of reliability

Variable	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted	Cronbach's Alpha
IE1	0.700	0.876	
IE2	0.760	0.850	0.886
IE3	0.796	0.836	
IE4	0.756	0.851	
TP1	0.663	0.867	
TP2	0.748	0.788	0.859
TP3	0.793	0.747	
PCO1	0.462	0.737	
PCO2	0.613	0.647	0.747
PCO3	0.581	0.666	
PCO4	0.520	0.701	
PV1	0.755	0.901	
PV2	0.838	0.873	0.912
PV3	0.831	0.875	
PV4	0.780	0.893	

4.3 Confirmatory Factor Analyses

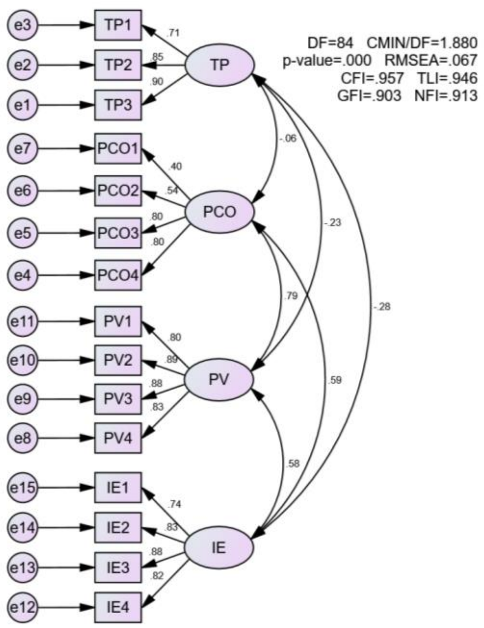

Figure 2. Confirmatory factor analysis model

Table 3. Results of the confirmatory factor analysis

The path			Estimate	S.E.	C.R.	P	CR	AVE
TP1	<---	TP	1					
TP2	<---	TP	1.204	0.11	10.899	***	0.864	0.682
TP3	<---	TP	1.202	0.109	10.993	***		
PCO1	<---	PCO	0.593	0.114	5.223	***		
PCO2	<---	PCO	0.743	0.103	7.196	***	0.737	0.430
PCO3	<---	PCO	1.098	0.1	10.954	***		
PCO4	<---	PCO	1					
PV1	<---	PV	0.916	0.069	13.206	***		
PV2	<---	PV	1.031	0.066	15.545	***	0.914	0.726
PV3	<---	PV	1.109	0.072	15.358	***		
PV4	<---	PV	1					
IE1	<---	IE	1					
IE2	<---	IE	0.988	0.087	11.403	***	0.864	0.682
IE3	<---	IE	1.053	0.087	12.049	***		
IE4	<---	IE	0.966	0.086	11.289	***		

Note: *** $p < 0.001$, standard error (S.E.), composite reliability (CR), average variance extraction (AVE)

Table 4. Correlation analysis

Variable	IE	TP	PCO	PV
IE	1			
TP	-0.253**	1		
PCO	0.441**	-0.014	1	
PV	0.522**	-0.213**	0.609**	1

Note: ** Correlation is significant at the 0.01 level.

The confirmatory factor analysis results (Figure 2) demonstrated that a factor loading exceeding 0.36 was an acceptable value. Subsequently, based on the factor loading (Table 3), CR and AVE were employed to evaluate the structural reliability and convergent validity of the data. A CR greater than 0.6 indicates acceptable convergent validity, and an AVE greater than 0.5 indicates good structural reliability of the latent variables. CR values in this study ranged from 0.737 to 0.914, indicating that the internal consistency reliability quality met the standards. AVE values ranged from 0.430 to 0.726, indicating that all items in each latent variable were consistent in explaining the latent variable. Table 4 shows that most of the correlations among variables are significant.

4.4 Hypotheses Testing

The collected data were utilized to validate the structural model. Table 5 illustrates that the model's overall fit index was deemed acceptable, as the findings fell within the generally accepted range. Specifically, the chi-square/ Degrees of Freedom (DF) was 1.880, Comparative Fit Index (CFI) was 0.957, Tucker-Lewis Index (TLI) was 0.946, Goodness-of-Fit Index (GFI) was 0.903, Normed Fit Index (NFI) was 0.913, standardized root mean square residual (SRMR) was 0.053, and Root Mean Square Error of Approximation (RMSEA) was 0.067. These data indicated that the model fit well and closely reflected the actual situation, revealing the overall level. Consequently, the study proceeded to compute the path coefficients.

Table 6 reveals that the majority of path coefficients calculated are statistically significant. The findings demonstrate that TP is significantly and negatively associated with IE, supporting H1 (H1: $\beta = -0.218$, $p < 0.05$). Thus, H1 is accepted. PCO is positively related to IE, supporting H2 (H2: $\beta = 0.432$, $p < 0.05$). Hence, H2 is accepted. However, there is no significant correlation between PV and IE, rejecting H3 (H3: $\beta = 0.184$, $p > 0.05$). Therefore, H3 is not accepted. Figure 3 provides a more intuitive representation of the data results for the research model.

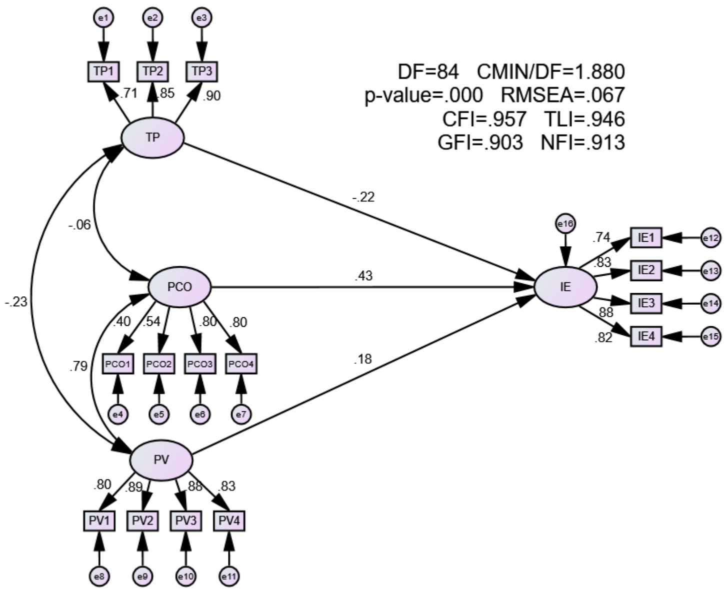

Figure 3. Structural model of the study

Table 5. Fitting index

Index	χ^2/df	CFI	TLI	GFI	NFI	SRMR	RMSEA
Reference Value	<3	>0.9	>0.9	>0.8	>0.8	<0.08	<0.08
	1.880	0.957	0.946	0.903	0.913	0.053	0.067

Table 6. Test results

Path relationship			Standardized estimate	S.E.	C.R.	P	Results
TP	→	IE	-0.218	0.074	-2.94	0.003	Supported
PCO	→	IE	0.432	0.188	2.897	0.004	Supported
PV	→	IE	0.184	0.161	1.293	0.196	Not Supported

4.5 Regression Analysis

Table 7 predicts the dependent variable IE and includes three independent variables, TP, PCO, and PV. By interpreting the indicators, it can be found that the coefficients of TP, PCO, and PV on IE are -0.153, 0.295, and 0.394, respectively, with PV having the most significant impact, with a standardized coefficient of 0.346. Simultaneously, the standardized coefficient of PCO also indicates a strong positive impact on IE. The intercept term B in the model is 1.494, indicating that the predicted value of the dependent variable is 1.494 when all independent variables are 0. The significant t-statistics of each independent variable are all greater than 2, indicating that they have a significant impact on IE. The collinearity test results show that there is no strong multicollinearity between the independent variables, and their tolerance VIF values are all less than 2, which meets the requirements of the model.

Table 7. Regression analysis

Coefficient[a]								
Model		**Unstandardized coefficients**		**Standardized coefficients**	**t**	**p-value**	**Collinearity statistics**	**VIF**
		B	**Std. error**	Beta			Tolerance	
1	(Constant)	1.494	0.334		4.475	0.000		
	TP	-0.153	0.053	-0.176	-2.868	0.005	0.933	1.071
	PCO	0.295	0.098	0.228	3.017	0.003	0.615	1.627
	PV	0.394	0.088	0.346	4.473	0.000	0.587	1.704

a. Dependent: IE

5. Discussion

In the present study, it was determined that after training college students to use ChatGPT, their perceived competence had a significant positive impact on their interest-enjoyment, indicating a relationship between these two variables. To effectively utilize ChatGPT as a learning tool, college students must demonstrate strong perceived competence. This entails accurately describing their problems to facilitate better understanding by the robot and providing targeted answers. Students must also carefully analyze and evaluate the robot's answers to assess their reliability and applicability, while asking further questions as needed. If the robot fails to comprehend the student's problem, the student should assist the robot in better perceiving their goal by reformulating their expressions and offering additional background information. Enhanced perceived competence in using ChatGPT allows college students to effectively comprehend and master pertinent information and key points of the target activity, resulting in more accurate and efficient responses. This improvement in perceived competence can boost college students' confidence and sense of achievement, thereby fostering an increase in their interest-enjoyment.

Through structural equation model path analysis, this study found that students' perceived value did not significantly impact their interest-enjoyment. However, regression analysis revealed that perceived value still exerted some influence on students' interest-enjoyment. This suggests that while the causal relationship between perceived value and interest-enjoyment may be weak when using ChatGPT as a learning tool, a correlation between the two exists. College students might lack a profound understanding of ChatGPT's importance and significance, or their ability to use the tool may be insufficient. Consequently, further enhancement of students' proficiency in using the tool is required, and the integration of the tool and learning should be considered by teachers.

Furthermore, this study discovered that pressure significantly affected the use of ChatGPT, but was negatively correlated with interest-enjoyment. Specifically, a negative correlation between tension-pressure and interest-enjoyment implies that college students' interest and pleasure in using ChatGPT surpass their tension-pressure levels, thus contributing to improved self-motivation and self-regulation. In particular, when college students are interested and engaged in using ChatGPT as a learning aid, they often do not feel stressed or anxious, as they believe they can become familiar with or utilize the tool to enhance their learning outcomes. Conversely, when college students are uninterested in or incapable of mastering ChatGPT, they frequently experience a certain degree of stress or anxiety.

By employing empirical research methods, this study confirmed its objective: to ascertain whether college students could learn to use ChatGPT as an auxiliary learning tool to satisfy three basic needs, namely autonomy, competence, and interpersonal relationships, and whether these needs directly affected their interest-enjoyment, which in turn influenced their learning motivation. The findings of this study can provide a novel perspective for schools or teachers to cultivate college students' proficiency in using ChatGPT to augment their interest-enjoyment in learning and ultimately enhance their learning motivation.

In conclusion, the research hypothesis that college students can learn to use ChatGPT as an auxiliary learning tool to meet three basic needs-autonomy, competence, and interpersonal relationships—has been confirmed by this study. These needs directly affect their interest-enjoyment, which in turn influences their learning motivation. The findings have several practical implications for the field of education, as well as specific recommendations for educators, educational administrators, and researchers.

6. Conclusion

In conclusion, this study aimed to analyze the impact of ChatGPT as an auxiliary learning tool on college students' learning motivation, using the framework of self-determination theory. The results demonstrated that tension-pressure, perceived competence, and perceived value, which measure three basic needs, had a significant influence on learning motivation after students learned to use ChatGPT. It was observed that an increase in stress and pressure led to a decrease in interest-enjoyment, whereas perceived competence in using ChatGPT and an understanding of the importance of artificial intelligence positively affected learning motivation.

The majority of participants reported using ChatGPT for less than 60 minutes per week, indicating that either they perceived limited assistance from this tool, or they were not fully aware of its importance. This suggests a need for further guidance in the use of ChatGPT. To effectively integrate ChatGPT into educational settings, it is crucial for educators and administrators to develop clear guidelines addressing data privacy, ethical considerations, and responsible use of the technology. Providing training and support to teachers and students is essential to ensure awareness of these guidelines and effective, responsible use of ChatGPT.

The potential of ChatGPT to support personalized learning experiences, cater to diverse student needs, enhance learning outcomes, and provide additional support to students with learning disabilities or those studying in a second language has been highlighted. However, the effectiveness of ChatGPT in educational settings should be evaluated through quantitative and qualitative research methods, including surveys, interviews, and assessments. Gathering feedback from teachers and students can help ensure that ChatGPT meets their needs and expectations.

It is important to acknowledge the limitations of this study, primarily the fact that the data sample was derived from China and the sample size was relatively small. As a result, the relationships between variables may not be significant, and increasing the sample size could yield more robust data. Additionally, the findings may not be generalizable to broader contexts or countries outside of China. Future research should consider increasing the sample size and expanding the target population, incorporating evaluations from teachers, and incorporating qualitative dimensions, such as in-depth interviews, to further explore specific factors contributing to the data.

Funding

We are grateful for the financial support from Qinghai University Teaching Mastery Training Programme.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

References

Chiu, T. K., Moorhouse, B. L., Chai, C. S., & Ismailov, M. (2023). Teacher support and student motivation to learn with Artificial Intelligence (AI) based chatbot. *Int. Learn. Environ.*, 1-17. https://doi.org/10.1080/10494820.2023.2172044.

Cotton, D. R., Cotton, P. A., & Shipway, J. R. (2023). Chatting and cheating: Ensuring academic integrity in the era of ChatGPT. *Innov. Educ. Teach. Int.*, 1-12. https://doi.org/10.1080/14703297.2023.2190148.

Deci, E. L. & Ryan, R. M. (1985). The general causality orientations scale: Self-determination in personality. *J. Res. Pers.*, *19*(2), 109-134. https://doi.org/10.1016/0092-6566(85)90023-6.

Ebadi, S. & Amini, A. (2022). Examining the roles of social presence and human-likeness on Iranian EFL learners' motivation using artificial intelligence technology: A case of CSIEC chatbot. *Int. Learn. Environ.*, 1-19. https://doi.org/10.1080/10494820.2022.2096638.

Flanagin, A., Bibbins-Domingo, K., Berkwits, M., & Christiansen, S. L. (2023). Nonhuman "Authors" and

implications for the integrity of scientific publication and medical knowledge. *JAMA*, *329*(8), 637-639. https://doi.org/10.1001/jama.2023.1344.
Gagné, M. & Deci, E. L. (2005). Self-determination theory and work motivation. *J. Organ. Behav.*, *26*(4), 331-362. https://doi.org/10.1002/job.322.
Gilson, A., Safranek, C. W., Huang, T., Socrates, V., Chi, L., Taylor, R. A., & Chartash, D. (2023). How does CHATGPT perform on the United States medical licensing examination? The implications of large language models for medical education and knowledge assessment. *JMIR Med. Educ.*, *9*(1), e45312. https://doi.org/10.2196/45312.
Gilson, A., Safranek, C., Huang, T., Socrates, V., Chi, L., Taylor, R. A., & Chartash, D. (2022). How well does ChatGPT do when taking the medical licensing exams? The Implications of Large Language Models for Medical Education and Knowledge Assessment. *medRxiv*, 2022.12.23.22283901. https://doi.org/10.1101/2022.12.23.22283901.
Gopalan, V., Bakar, J. A. A., Zulkifli, A. N., Alwi, A., & Mat, R. C. (2017). A review of the motivation theories in learning. *AIP Conf. Proc.*, *1891*(1), 020043. https://doi.org/10.1063/1.5005376.
Heaven, D. (2020). Why faces don't always tell the truth about feelings. *Nature*, *578*(7796), 502-505.
Kasneci, E., Seßler, K., Küchemann, S., Bannert, M., Dementieva, D., Fischer, F., & Hüllermeier, E. (2023). ChatGPT for good? On opportunities and challenges of large language models for education. *Learn. Individ. Differ.*, *103*, 102274. https://doi.org/10.1016/j.lindif.2023.102274.
Krapp, A. (1999). Interest, motivation and learning: An educational-psychological perspective. *Eur. J. Psychol. Educ.*, *14*, 23-40.
Kung, T. H., Cheatham, M., Medenilla, A., Sillos, C., De Leon, L., Elepaño, C., Madriaga, M., Aggabao, R., Diaz-Candido, G., Maningo, J., & Tseng, V. (2023). Performance of ChatGPT on USMLE: Potential for AI-assisted medical education using large language models. *PLoS Dig. Health*, *2*(2), e0000198. https://doi.org/10.1371/journal.pdig.0000198.
Kuo, Y. C., Walker, A. E., Schroder, K. E., & Belland, B. R. (2014). Interaction, Internet self-efficacy, and self-regulated learning as predictors of student satisfaction in online education courses. *Int. High. Educ.*, *20*, 35-50. https://doi.org/10.1016/j.iheduc.2013.10.001.
McAuley, E., Duncan, T., & Tammen, V. V. (1989). Psychometric properties of the Intrinsic Motivation Inventory in a competitive sport setting: A confirmatory factor analysis. *Res. Q. Exerc. Sport*, *60*(1), 48-58. https://doi.org/10.1080/02701367.1989.10607413.
Mhlanga, D. (2023). Open AI in education, the responsible and ethical use of ChatGPT towards lifelong learning. *SSRN*. http://dx.doi.org/10.2139/ssrn.4354422.
Okonkwo, C. W. & Ade-Ibijola, A. (2021). Chatbots applications in education: A systematic review. *Comput. Educ. AI*, *2*, 100033. https://doi.org/10.1016/j.caeai.2021.100033.
Reeve, J. (2009). Why teachers adopt a controlling motivating style toward students and how they can become more autonomy supportive. *Educ. Psychol.*, *44*(3), 159-175. https://doi.org/10.1080/00461520903028990.
Rudolph, J., Tan, S., & Tan, S. (2023). ChatGPT: Bullshit spewer or the end of traditional assessments in higher education? *J. Appl. Learn. Teach.*, *6*(1), Article ID: 9. https://doi.org/10.37074/jalt.2023.6.1.9.
Ryan, R. M. & Deci, E. L. (2000). Intrinsic and extrinsic motivations: Classic definitions and new directions. *Contemp. Educ. Psychol.*, *25*(1), 54-67. https://doi.org/10.1006/ceps.1999.1020.
Ryan, R. M. & Deci, E. L. (2020). Intrinsic and extrinsic motivation from a self-determination theory perspective: Definitions, theory, practices, and future directions. *Contemp. Educ. Psychol.*, *61*, 101860. https://doi.org/10.1016/j.cedpsych.2020.101860.
Sallam, M. (2023). The utility of ChatGPT as an example of large language models in healthcare education, research and practice: Systematic review on the future perspectives and potential limitations. *medRxiv*, 2023.2002. 2019.23286155. https://doi.org/10.1101/2023.02.19.23286155.
Sánchez-Oliva, D., Palmeira, A. L., Carraça, E. V., Teixeira, P. J., Markland, D., & Silva, M. N. (2021). Motivational strategies used by exercise professionals: A latent profile analysis. *J. Phys. Act. Health*, *18*(8), 895-903. https://doi.org/10.1123/jpah.2020-0338.
Sheldon, K. M. & Elliot, A. J. (1999). Goal striving, need satisfaction, and longitudinal well-being: The self-concordance model. *J. Pers. Soc. Psychol.*, *76*(3), 482-497. https://doi.org/10.1037/0022-3514.76.3.482.
Stokel-Walker, C. (2022). AI bot ChatGPT writes smart essays-should academics worry? *Nature*. https://doi.org/10.1038/d41586-022-04397-7.
Vansteenkiste, M., Sierens, E., Goossens, L., Soenens, B., Dochy, F., Mouratidis, A., & Beyers, W. (2012). Identifying configurations of perceived teacher autonomy support and structure: Associations with self-regulated learning, motivation and problem behavior. *Learn. Instr.*, *22*(6), 431-439. https://doi.org/10.1016/j.learninstruc.2012.04.002.
Vázquez-Cano, E., Mengual-Andrés, S., & López-Meneses, E. (2021). Chatbot to improve learning punctuation in Spanish and to enhance open and flexible learning environments. *Int. J. Educ. Technol. High. Educ.*, *18*(1), 1-20. https://doi.org/10.1186/s41239-021-00269-8.

Yin, J., Goh, T. T., Yang, B., & Xiaobin, Y. (2021). Conversation technology with micro-learning: The impact of chatbot-based learning on students' learning motivation and performance. *J. Educ. Comput. Res., 59*(1), 154-177. https://doi.org/10.1177/0735633120952067.

Zhai, X. & Center, A. S. E. (2023). ChatGPT and AI: The game changer for education. Available at *SSRN*: https://ssrn.com/abstract=4389098