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The Impact of AI-Driven Personalized Learning and Curriculum Design on Student Engagement in Chinese Higher Education

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Abstract

The rapid advancement of Artificial Intelligence (AI) has significantly impacted various sectors, including higher education. The advancement of technology has urged a necessity for the development of AI-driven personalised learning in an attempt to foster a greater degree of student engagement, encourage a student-centred learning approach as well as the creation of adaptive learning systems. This research addresses how AI-based personalized learning and curriculum design can affect higher education as well as how it helps to engage students in China. It is grounded in Self Determination Theory and is an examination of the ways in which AI can improve autonomy, competence, relatedness, and motivation, in addition to the concepts of Herzberg's Two-Factor theory. In closing, the study fills research gaps with an analysis of how AI was aligned with China's educational policies.The survey of 423 university students will take place in the study and the IBM SPSS software will be used for the collection data. It is expected that the relationship between each of the aspects of the AI-based personalized learning will be observed after the research and the outcome can be helpful for the policymakers. The study enhances student engagement by fostering autonomy, competence, and motivation, as explained through SDT and Herzberg's theory. Some suitable strategic and practical recommendations include faculty training, robust infrastructure, and industry collaboration, ensuring equitable, dynamic, and effective curriculum design are also involved for further improvement.

Keywords: Personalised Learning, Feedback, Psychological Needs, Learning Environments, Competency

Introduction

Research Background

Artificial intelligence (AI) in the global context has been reshaping the educational landscape with the offering of personalised experience catering to the unique needs of diverse students. National education reforms and digital transformation related initiatives in China have also increased the adoption of AI tools and technologies in schools as well as universities. These integrations are aligned with global trends towards student-centric pedagogy. In the schools and universities of China, AI-driven personalised learning and curriculum design for higher education promises to revolutionise student engagement by providing learning experiences that fit individual preferences and needs (Yan et al., 2025). AI can analyse the weaknesses, strengths, and learning styles of the students to develop customized learning processes with effective content and support to confirm whether the students are getting proper sources of knowledge.

All these features of AI including content personalization, adaptive feedback, and real-time progress tracking are also related to SDT constructs. This is because personalisation supports autonomy whereas difficulty improves competency. Interactive tools such as chatbots have also been found to be fostering relatedness through simulated social pressures. Recent surveys in the context of the Chinese higher education system have also indicated that more than 70% of students have reported a rise in their motivation whenever they use AI-based platforms (Xiaowen et al., 2025). Therefore, this study here is focussed on exploring how AI-powered learning environments in Chinese higher education can be designed for supporting SDT constructs and further improves student engagement.

Research Issues

It is possible that AI-driven curricula can be used for supporting the personalised needs of students, relevant to their autonomy, competence and relatedness, allowing them to take control over their learning file. These psychological needs which include autonomy, competence and relatedness are crucial parts of self-determination theory. Despite rapid digital transformation in the Chinese education sector, student disengagement persists to be a pressing issue. Reports from the Ministry of Education have indicated that motivation levels among secondary and tertiary students have reduced by 18% in the last three years (Wang et al., 2022). The dropout rates in some rural universities have also reached 12%.

AI-driven personalised learning is effective and beneficial for student engagement as it helps to design the curriculum and improves academic performance. In response to this, China's 2025 national guideline on accelerating education digitalization has been promoting AI integration for improving critical thinking and problem-solving skills (Jiang, Shang & Jiao, 2023). Hence, the central issue of the study is to address the gap between the theoretical potential of AI to support SDT based engagement and the practical limitations in teacher readiness. Even though the past literature has highlighted the benefits of AI in personalised learning, very few studies have pointed towards the Chinese context of AI enabled environments. The current research, hence, seeks to fill that gap and explore the conditions under which AI can be effectively used for improving student engagement in higher education. In order address this research gap, the researcher developed some research questions that are following:

RQ1: How do autonomy, competence and relatedness influence student engagement in AI-based learning?
RQ2: Does motivation mediate the relationship between psychological needs and student engagement?
RQ3: What institutional and pedagogical barriers affect the implementation of AI-driven personalised learning in China?
RQ4: What design strategies can enhance AI-based learning engagement aligned with SDT?

Significance of Study

The study topic, which is related to the effect of AI-driven learning, is significant as it can help the teachers to increase the learning experience of the students by enhancing their learning experience through better autonomy, competence and relatedness of the curriculum. This is aligned with the self-determination theory (SDT) which posits that fulfilling these psychological needs is crucial for greater intrinsic motivation and student engagement. Even though the SDT has been widely used in traditional learning contexts, its integration with AI-enabled learning environments is still quite scarce. This is specifically true in the context of the Chinese higher education system. The current study hence is addressing this gap and linking AI functionalities to the motivation theory. It acts as an innovative application in education that represents educational materials through interesting factors like games, simulation, and others, as it makes the learning process more engaging and fun. The current study is also offering insights for the educators into how AI tools can be used for personalising instructions, adapting teaching strategies in real-time as well as monitoring student progress. The findings of the study is also highlighting the importance of teacher training needed for maximising the benefits of AI-driven learning.

Literature Review

Theoretical Framework

The study employs two theories, including Self-Determination Theory and Herzberg's Two-Factor Theory. The framework developed by Deci and Ryan (1985), known as Self-Determination Theory (SDT), explains that the pursuit of autonomy, competence, and relatedness drives the motivation to act. SDT frames AI-driven personalisation as a process to satisfy the basic psychological needs. In terms of autonomy, AI provides customisable goals and choices, enhancing perceived volition for maintaining transparency. Maintaining competence is useful for scaffold practices and adaptive diagnostics as it provides challenging tasks and formative feedback with progress. In case of relatedness, peer-group matching, conversational agents, and teacher dashboards can sustain social belonging and connection. Therefore, AI must support internalisation by avoiding coercive nudges, which can reduce intrinsic motivation and undermine autonomy.

For instance, as mentioned in the study conducted by Chiu (2024), AI can be used for monitoring engagement patterns and adapting instructional strategies in real-time. Hence, as mentioned in the study conducted by Marylène Gagné et al. (2022), AI aligns curriculum delivery with motivational profiles of each student. This dynamic responsiveness is crucial for fostering sustained intrinsic motivation among students as well. AI can deliver just-in-time scaffolds for competence growth, which can be used in sequence tasks at the zone of learners for proximal development to prevent overload and adjust pacing. However, the real-time analytics guide micro feedback and recommended systems to support the improvement of sustained engagement and self-efficacy when overseen by the instructors.

According to Herzberg's Two-Factor Theory, motivation among individuals arises when a sense of achievement or recognition through feedback from AI systems is achieved through the usage of AI for curriculum development and results in student engagement (Ibrahim et al., 2023). This theory guides AI-driven curriculum design by differentiating between hygiene factors and motivators that influence student engagement. In this framework of Herzberg, the hygiene factors prevent dissatisfaction but do not create motivation. When this theory is implemented in the context of education, it relates closely to the theory of self-determination, focusing on competence, autonomy, and relatedness. This model is very important in evaluating the impact of AI models on the education environment of the student and then enthusiasm towards learning (De-Juan-Vigaray et al., 2024). Herzberg's Two-Factor Theory is suitable to understand educational motivation because it helps to separate satisfaction enhancers from dissatisfaction preventers by reflecting the learning experience of the students.

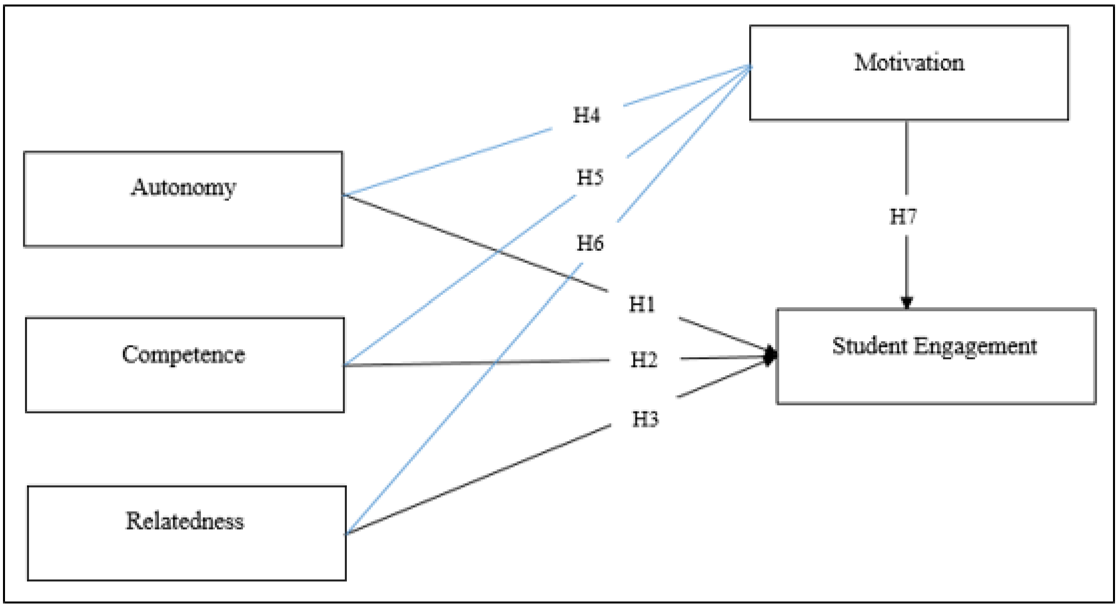

Fig. 1 Framework of Research

The above fig. 1 represents the relationship between variables by this conceptual framework. Here, motivation acts as a mediator because it helps to change the psychological needs of competence, autonomy, and relatedness into active student engagement. Based on the self-determination theory, these three factors help to maintain the standard of human means, which enhances intrinsic motivation. In the absence of motivation, the relationship between engagement and all these requirements would be incomplete, as motivation provides psychological growth for the satisfaction of needs. Therefore, motivation logically develops a connection between SDT factors and engagement to explain how these requirements can fulfil sustained academic participation.

In adherence with the SDT, Han (2021) has asserted that students in general have three important necessities, which are autonomy, capability, and belongingness, and proceeded to address autonomy as an indicator of changes in engagement. Reflecting on the viewpoints of Pedler, Hudson & Yeigh (2020) it can be expressed that instruction that provides support for student autonomy and effective use of participation structures is estimated to be the most effective learning environment for cognitive engagement.
H1: Autonomy has a significant impact on student engagement.

Chiu (2021) has expressed that technological learning environments must be supportive of students' requirements as it not only fosters competence but motivates engagement and optimises student learning. Wang & Hofkens (2020) have remarked that

student engagement is a protective asset that decreases the likelihood of adolescents engaging in problem behaviours other than increasing academic competence.
H2: Competence has a significant impact on student engagement.

According to Chiu (2021), students are more likely to experience a greater degree of psychological well-being upon feeling connected, loved, and interacted with. Relatedness often serves as a predictor of emotional, behavioural, and engagement as it gives students the confidence to complete challenging tasks and encourages them to seek their educational needs.
H3: Relatedness has a significant impact on student engagement.

Motivation among students has been related to academic achievements, drop-out intentions, effort, and drop-out intentions along with learning as a whole wherein students experiencing autonomy support are more likely to achieve better grades (Johansen, Eliassen & Jeno 2023). Furthermore, Jehanghir, Ishaq & Akbar (2024) have highlighted that one of the keys aims of higher education is fostering autonomy among students, and students exercising greater control over their learning have a greater propensity of benefiting from a higher degree of motivation.
H4: Autonomy has a significant impact on motivation.

Competence has been referred to as paramount in terms of fostering a sense of self-efficacy and enthusiasm for learning alongside the development of emotional resilience. Liu, Zhao & Su (2022) have opined that the cognitive and motivational competences of teachers are imperative to the educational outcomes of students in digital learning settings.
H5: Competence has a significant impact on motivation.

According to the viewpoints of Capon-Sieber et al. (2022), teachers' relatedness-supportive behaviour is a major determinant of students' intrinsic motivation and is a significant driver of student motivation. A similar vein of opinions is reflected in the views of Bureau et al. (2022) who have stated that relatedness is not only key to the development of intrinsic motivation but confidence among the pupils as well.
H6: Relatedness has a significant impact on motivation.

Student motivation and engagement are essentially multifaceted and complex concepts and are often influenced by a variety of internal and external factors. According to Shin & Bolkan (2021), one of the significant drivers of motivation among students is intellectual stimulation, the benefits of which are incurred in terms of student engagement and a greater degree of attention.
H7: Motivation has a significant impact on student engagement.

The gaps identified overall from the study conducted can be divided into the theoretical, methodological and contextual gaps. The significant theoretical gap of the study should be discussed first. Therefore, addressing these identified gaps can be done through testing a model, where AI-driven personalization influences engagement through autonomy, motivation, relatedness and motivation.

Methodology

The research has been conducted based on the quantitative research design. The quantitative research design has been employed for this study that helps to interpret all of the information in a statistical way. Furthermore, the researcher can also be capable of observing and measuring individual items in a statistical way. It is expected that incorporation of quantitative research design will be associated with benefits such as enabling researchers to gather data from a large number of the population (Thomas & Zubkov, 2023). The chances of conducting bias-free research are also higher while a quantitative research design method is used in a study. The target population for this study consists of the students as mentioned in the academic levels who are studying in the Peking University, Beijing. This university is known to currently have around 50,000 students in total at different academic levels. A “Krejcie & Morgan” table is employed in this case to gain an idea about the appropriate size of sample in respect to the huge population. The adjacent sample size in the table for the chosen target population is 381 (nursesrevisionuganda.com. 2023). This sample size in the table is corresponding to a 95% confidence level, which signifies a 5% margin of error.

This is also assuming a medium effect size which is suitable for a population like the one chosen in this study. Considering this, to reduce the chance of non-response bias, the researchers selected 423 sample sizes in this case to enhance the scope of this research. In addition, the primary data collection is suitable for the study in terms of generating various types of insights about the aspects covered under the study. The chances of getting new insight are also high in this case because the data collection will be first-hand by nature. The data collection method is considered more effective in this case compared to the secondary data collection method, because the secondary data collection method is not very effective to provide ideas about the current scenario regarding the AI-use in personalized learning.

The data collection was conducted between July and August of 2025. The distribution of the survey questionnaire was controlled by limiting the access to all the verified student email lists and university affiliated social media groups. A response rate of 100% has been noted in this study. The primary data collection done in the study and a quantitative research design is incorporated to conduct it. Hence, the quantitative data analysis method used for the study in terms of getting effective insights based on the purpose of the study. The relationship between the variables can also be established through the study outcome and the data analysis. Hypotheses were developed based on the review of previous research works (Ghanad, 2023). It stated that usage of IBM SPSS is supportive for conducting regression tests or descriptive statistical analysis in terms of gaining valuable insight. Apart from this, the test of reliability (Cronbach alpha) and validity (Pearson’s Correlation Coefficient) was done with data analysis procedures. Furthermore, the Sobel test was also conducted to identify the mediating impact of motivation on the relationship between AI-driven personalised learning and curriculum design on student engagement.

The test that is to be accomplished under the quantitative data analysis, mainly includes the regression test as well as the descriptive statistics test. Descriptive statistical tests are helpful for the investigation of the central tendency as well as the assessment of mean or median is done through these tests (Bulanov et al., 2021). A five-point Likert scale has been used in this study along with the questionnaire that are used for the survey purpose. For the specific study the options should be - “1 = strongly disagree”, “2 = disagree”, “3 =

neutral", "4 = agree "and "5 = strongly agree". Variables like student engagement are measured through items adapted from the study by Cifuentes & Valverde (2024). The items do Autonomy have been adapted for the study by Farikah et al. (2023). All of the items for Competence have been adapted from the study by Simons, Meeus & T'Sas (2017). Relatedness has been measured using items like "I can relate to several of my classmates in this class" that have been adapted from the study by Goldman, Goodboy & Weber (2017). The opinions are to be measured using the five-point Likert scale. Motivation is being measured by the items adapted from the article by (Agustina, Wahyudin & Pratiwi 2021) including items like "I feel that learning is useful for me in the future". This research shall be carried out in compliance with the Personal Information Protection Law (PIPL) in China where the anonymity and autonomy of the participants are assured. All of the data are kept confidential to avoid deceiving or misleading participants about the purpose of the study.

Results of Analysis

Sample Characteristics and Data Distribution

A total of 423 valid questionnaires have been collected to analyse the connections between the variables, as shown in

Table **1,** which depicts the demographic characteristics of the study within the responses of 423 respondents. In this context, the largest group is 20–25 years with 43.3% followed by 26–30 years with 33.1%. The highest number of individuals belonging to the 20 to 25 years age group indicates that they are highly exposed to the usage of AI in the field of learning. Meanwhile, gender distribution is relatively balanced with 216 males at 51.1% and 207 females at 48.9%.

Table 1
Demographic Profiling Test

		Count	Column N %
Age	20-25 years	183	43.3%
	26-30 years	140	33.1%
	31-35 years	51	12.1%
	Above 35 years	49	11.6%
Gender	Female	207	48.9%
	Male	216	51.1%
Discipline	Engineering	68	16.1%
	Computer science	83	19.6%
	Business / Management	191	45.2%
	Medical or Health Sciences	59	13.9%
	Humanities	22	5.2%
Institution type	Public university	174	41.1%
	Private university	249	58.9%

Based on the academic discipline, the majority of the respondents come from a management or business background, with 45.2% followed by computer science, Engineering, and Medical Science with 19.6%, 16.1%, and 13.9% respectively. It also highlights the humanities, with 5.2% accounting for the smallest group. Therefore, it can be stated that the business management student gets more exposed to the use of AI-assisted learning, which improves their engagement level towards their learning.

Measurement of Model Evaluation

Reliability and Validity

Cronbach's Alpha and Pearson's Correlation Coefficient tests were conducted on every potential variable of the questionnaire, and the outcomes are demonstrated in

Tables **2** and **3,** which identified that the value for Cronbach's alpha is 0.959. It refers to that all of the items are highly reliable.

Table 2

Cronbach's Alpha Statistics for Reliability Analysis

Reliability Statistics		
Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.959	.959	5

The Cronbach alpha value standardised items is 0.959, which indicates that all of the items are highly correlated with each other and effective in measuring individual items. The result of the reliability test demonstrates that a high Cronbach's alpha helps to measure different items in the survey or questionnaire, such as autonomy, competence, relatedness, motivation, and engagement. It also enhances the validity for further hypothesis testing, H1 to H7. From the overall value, it can be expected that the construct-wise reliability is also supportive in this case, which results in the generation of a supportive overall value.

Validity Analysis

Pearson's correlation coefficient helps to figure out the correlation between variables. As per the result of Table 3, it has been pointed out that autonomy has a strong and positive correlation with student engagement, as its r value is 0.908. Additionally, it also has a strong positive relation with motivation, as its sig value is 0.897.

Table 3

Pearson's Correlation Coefficient Statistics for Validity Analysis

Correlations						
		A	C	R	M	SE
A	Pearson Correlation	1	.822**	.726**	.897**	.908**
	Sig. (2-tailed)		.000	.000	.000	.000
	N	423	423	423	423	423
C	Pearson Correlation	.822**	1	.837**	.899**	.757**
	Sig. (2-tailed)	.000		.000	.000	.000
	N	423	423	423	423	423
R	Pearson Correlation	.726**	.837**	1	.812**	.747**
	Sig. (2-tailed)	.000	.000		.000	.000
	N	423	423	423	423	423
M	Pearson Correlation	.897**	.899**	.812**	1	.815**
	Sig. (2-tailed)	.000	.000	.000		.000
	N	423	423	423	423	423
SE	Pearson Correlation	.908**	.757**	.747**	.815**	1
	Sig. (2-tailed)	.000	.000	.000	.000	
	N	423	423	423	423	423

****. Correlation is significant at the 0.01 level (2-tailed).**

Multiple Linear Regression Analysis

In the current study, multiple regression analysis is being used to determine how well a set of predictors, which are the independent variables and the mediating variable is have a relationship with the outcome variable, which is student engagement, as shown in

Table **4,** which indicates that a significant value less than 0.05 is generally considered to be significant. This is in consideration of a confidence interval of 95%.

Table 4
The Results of Multiple Regression Analysis

Coefficients[a]								
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	.114	.064		1.774	.077	-.012	.241
	A	.913	.043	.915	21.174	.000	.828	.998
	C	-.115	.050	-.111	-2.315	.021	-.212	-.017
	R	.308	.038	.289	8.039	.000	.232	.383
	M	-.139	.057	-.140	-2.435	.015	-.251	-.027
a. Dependent Variable: SE								

The significance value is calculated to be 0.000 for the variable autonomy, which shows a strong positive influence on student engagement. Furthermore, for the variable competence, the multiple regression model shows a significance value of 0.021, which is again less than 0.05. From the overall outcome, it can be stated that despite the differences observed in the obtained Sig. value, all are helpful to indicate a positive relationship between the dependent variable and the factor.

Mediating Effects for the Sobel Test

The Sobel test is conducted to evaluate if a mediating variable statistically mediates the relationship between an independent and a dependent variable, as shown in

Table 5
Sobel test for motivation and student engagement

Coefficients[a]								
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	.561	.085		6.586	.000	.394	.729
	M	.809	.028	.815	28.891	.000	.754	.865
a. Dependent Variable: SE								

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Table 6

Sobel test for motivation and autonomy

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	.293	.066		4.459	.000	.164	.423
	A	.901	.022	.897	41.585	.000	.858	.944

a. Dependent Variable: M

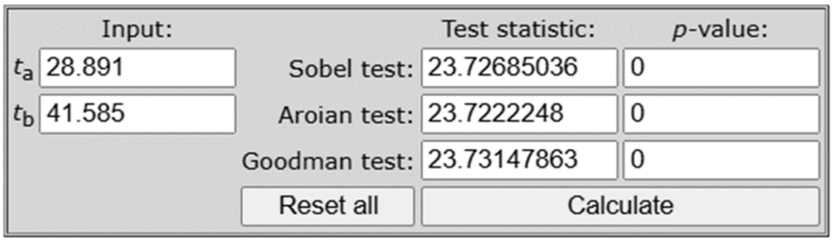

Fig. 2Sobel test for motivation and autonomy

Table 7

Sobel test for motivation and competence

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	.159	.068		2.342	.020	.026	.293
	C	.934	.022	.899	42.118	.000	.890	.977

a. Dependent Variable: M

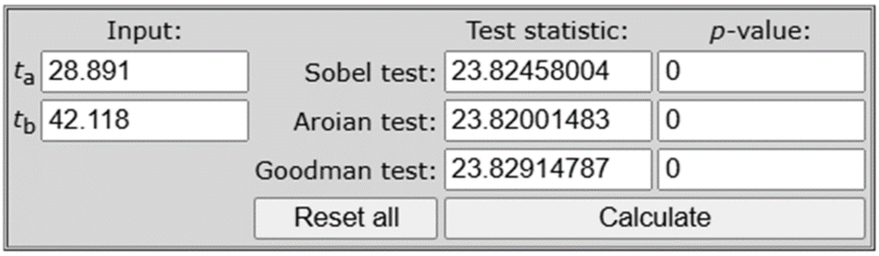

Fig. 3Sobel test for motivation and competence

Table 8
Sobel test for motivation and relatedness

Coefficients[a]								
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	.395	.092		4.301	.000	.214	.575
	R	.870	.030	.812	28.532	.000	.810	.930
a. Dependent Variable: M								

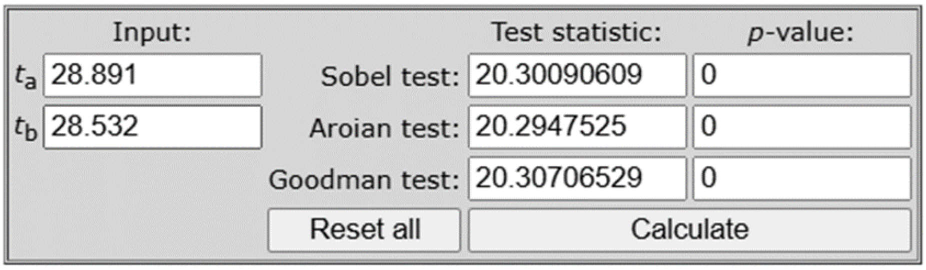

Fig. 4Sobel test for motivation and relatedness

In the context of this current research, “Motivation” has been referred to as the mediating variable. The outcomes in the following table highlight the interplay between the dependent variable, student engagement (SE), with that of motivation.

Conclusion

The study outcome helps in identifying that all the factors like autonomy, competence as well as relatedness in relation to the AI-driven personalised learning seems effective to improve engagement of students. The current study aimed to evaluate the impact of AI-driven personalised learning and curriculum design on student engagement in Chinese higher education. All the seven hypotheses were supported, which confirmed that autonomy, competence and relatedness have significant impact on both motivation as well as engagement. The outcome is generated considering the perspective of students mainly regarding AI-driven personalised learning. This form of student-centered perspective in the findings above have highlighted the necessity of designing AI systems which not only deliver content but also support emotional as well as social dimensions of learning.

This is further needed for supporting both practical as well as theoretical implications for AI integration in higher education. The study findings have extended SDT by empirically validating that AI-driven learning environments can satisfy all the three psychological needs: autonomy, competence and relatedness. This as per the findings mainly happens through digital personalisation. The same further reinforces the applicability of the theory in any technology-mediated learning contexts. Despite this, some limitations are observed within the study, which mainly includes its limitation or relevance to a specific region as well as it does not cover about the perspective of teachers in the context of student engagement. The new insight is generated based on the survey data-based outcome, issues like lack of in-depth idea or insufficient capturing the emotion of the student are significant issues in this matter.

Future studies must also focus on incorporating complementary frameworks like Technology Acceptance Model (TAM) or the Unified Theory of Acceptance and Use of Technology (UTAUT). The use of these theoretical frameworks can help explore how perceived usefulness and ease of use have an impact on engagement in AI mediated learning environments. In future, perspectives of the teachers should also be included for providing a more holistic view of AI integration. This is specifically needed regarding instructional design, perceived challenges of AI implementation, as well as professional development requirements. Along with this, future researchers on similar topics may try expanding the geographic location beyond Beijing and also include tier 2 and tier 3 cities or other vocational institutions. This can help reveal regional disparities in AI adoption as well as student engagement outcomes.

Ethical Statements
This study was conducted in accordance with institutional and international ethical research standards.

Statements and Declarations
All ethical, authorship, and data integrity requirements for publication have been fully met.

Competing Interests
The authors declare that they have no competing interests.

Informed Consent Statement
Informed consent was obtained from all individual participants involved in the study.

Author Contributions
All authors contributed equally to the study's conception, design, data collection, analysis, and manuscript preparation.

Artificial Intelligence (AI) Usage
Artificial intelligence tools were used solely for language refinement and grammatical editing, and did not influence the study design, analysis, or findings.

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