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Research on the Construction of Smart Teaching Mode with Artificial Intelligence Technology Facilitating Education Informatization in Colleges and Universities

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Abstracts

Based on subject knowledge mapping, this paper dynamically collects learning data, portrays learners' learning situations, and accurately regulates the learning process. Personalized learning path recommendations and learning communities are constructed through learner profiling and learning services. Secondly, structural equation modeling was used to hypothesize the three-level elements of the E-GPPE-C model. Finally, 103 college students in smart teaching classes were taken as research subjects, and the utility of the smart teaching model was analyzed separately through the steps of precondition validation and cross-lag model with random intercepts. The results show that the smart teaching model has β=0.286 for deep learning strategy, β=0.211 for the smart classroom, and β=0.20 for classroom participation, and they accurately indicate that smart teaching has a positive facilitating mechanism on the learning ability of college students. This study also provides a useful reference for the practice of smart teaching in various disciplines in colleges and universities.

Keywords: Artificial intelligence; E-GPPE-C model; Knowledge graph; Learner profiling; Structural equation modeling.
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1 Introduction

Traditional classroom teaching is limited by the limitations of educational concepts, organizational methods, educational means, and other aspects, and there are certain teaching dilemmas. Facilitated by artificial intelligence technology, college teaching presents an educational pattern from the pursuit of quantity to the pursuit of quality, from the same standard to individual analysis, from a single way to mixed teaching, from broad experience to precise feedback, and unidirectional output to interactive linkage [1-3]. 2021 The Notice on Strengthening the Informatization of Educational Management in the New Era, issued by the Ministry of Education in March 2021, explicitly states that “Strengthen the reform in the field of education, take new technology means as the driving force, and promote the intelligent change of education management” [4-6]. It can be seen that artificial intelligence technology will play an indelible influence in the field of teaching and learning innovation of college education informatization, which is an important hand in cracking the current teaching dilemma.

Informatization of education is aimed at promoting the intelligent transformation of education through the comprehensive and in-depth use of new-generation information technologies, such as “Internet+”, Virtual Reality Augmented Reality (VR/AR), Big Data, Cloud Computing, 5G, and Artificial Intelligence, in the educational sphere [7]. Gubchenko, A. and Romanova, V. examined the impact of informatization on the pedagogical traditions of the Russian military education system and found that the traditional pedagogical system is undergoing a “partial” transformation under the influence of e-learning, information and ICT educational technologies, etc. [8]. Liang, Z. et al. Education informatization improvement indicates the direction to build a ubiquitous learning environment and explore the role of big data in improving the quality of education, promoting the equity of education, optimizing the concept of education, etc. [9]. Jin, Y. et al. found that the rapid development of artificial intelligence and deep learning has made many universities and colleges put forward the goal of campus digitization and education informatization [10].

The research on the educational application of artificial intelligence started earlier and has a wider scope, mainly including theoretical research on educational artificial intelligence, research on AI teaching products, and research on AI to promote changes in classroom teaching and application in different disciplines [11]. Johnson, D. et al.’s research on the teaching of artificial intelligence towards the use of AI in the United Arab Emirates (UAE) found that it is mainly used for teaching through the understanding and analyzing the learning process to create conditions for student learning [12]. Liu, S. W. J. exploring the impact of AI on ice and snow talent development instruction, found that AI is putting smart teaching platforms to use to make students more active learners and emphasized that smart technologies can be integrated with the field of robotics [13]. Waldman, C. E. et al. proposed that the use of Artificial Intelligence (AI) in medical education curricula provides a framework for healthcare education. The study also provides a way to fill the gap of AI in medical education [14]. Bucea-Manea-Oni, R. et al. found that Serbia and Romania are adopting AI to be introduced into education, thus changing the lack of education in the region, and they explored the problems that exist when AI is used in teaching and learning and in what direction it will actually go [15].

After the concept of “Smart Earth” was put forward, many scholars at home and abroad began to explore how the new technology affects the field of education, and then they began the study of interactive teaching mode, which mainly focuses on the theory, design, application and evaluation of several aspects [16]. Gao, J. et al. proposed an online smart teaching system for cloud classrooms under a personalized recommendation system, which uses a collaborative filtering recommendation algorithm, thus stimulating the students’ interest in learning, and the teacher’s use of smart devices for teaching can largely improve the students’ classroom activity [17]. Huang, J. and Wang, T. constructed the framework of intelligent teaching through the design of the auxiliary system, optimized the traditional teaching mode by using network technology, and changed the external environment in order to make the learning process more pleasant and let the students' learning level improve [18]. Liu, Q. and Yang, Z. constructed the teaching platform integrating cloud application platform, resource platform, learning space, and interactive classroom by using the multimedia communication technology of the Internet of Things (IoT), resource platform, learning space, and interactive classroom as a whole, and the program provides technical support for designing an English smart classroom [19].

In this paper, the E-GPPE-C model of smart teaching is constructed with the support of artificial intelligence. The core of the operation of the model lies in the dynamic collection of learning data based on subject knowledge mapping, the portrayal of learner learning, and the precise regulation of the learning process. Through the support of learner profiling and learning services, personalized learning service recommendations include personalized learning paths and the construction of learning communities. Secondly, based on the use of the structural equation modeling method, empirical research is conducted on the causal generation and regulation and promotion role and specific path relationship between the three levels of elements of the E-GPPE-C model of smart teaching. Finally, taking 103 college students who attend classes in smart teaching as research subjects, the utility of the smart teaching model is analyzed separately through the steps of prerequisite validation and cross-lag modeling with random intercepts.

2 Intelligent teaching model based on subject knowledge mapping

This study proposes an AI-supported smart teaching model, which is based on AI technology and learning environment as the basic guarantee and subject knowledge mapping and learning big data as the core support, so as to support the development of learning services, such as learner profiling, learning paths, learning evaluation, etc., and ultimately to promote the wisdom of the learning community group development [20].

2.1 The E-GPPE-C Model of Smart Teaching and Learning

This study addresses six core elements: learning environment, subject knowledge mapping, learner portrait, learning path, learning evaluation, and learning community [21]. Abstracting the six keyword abbreviations of environment, mapping, portrait, path, evaluation, and community, the model is named as Smart Teaching E-GPPE-C model [22]. The conceptual map of subject knowledge mapping in the E-GPPE-C model is shown in Fig. 1, which utilizes machine learning techniques to construct the associative relationships among knowledge and knowledge, problem and problem, and competence and ability as well as the knowledge mapping problem and problem mapping competence mapping relationships. These knowledge, problem, and capability sets and the interrelationships among knowledge, problems, and capabilities are called discipline knowledge maps [23].

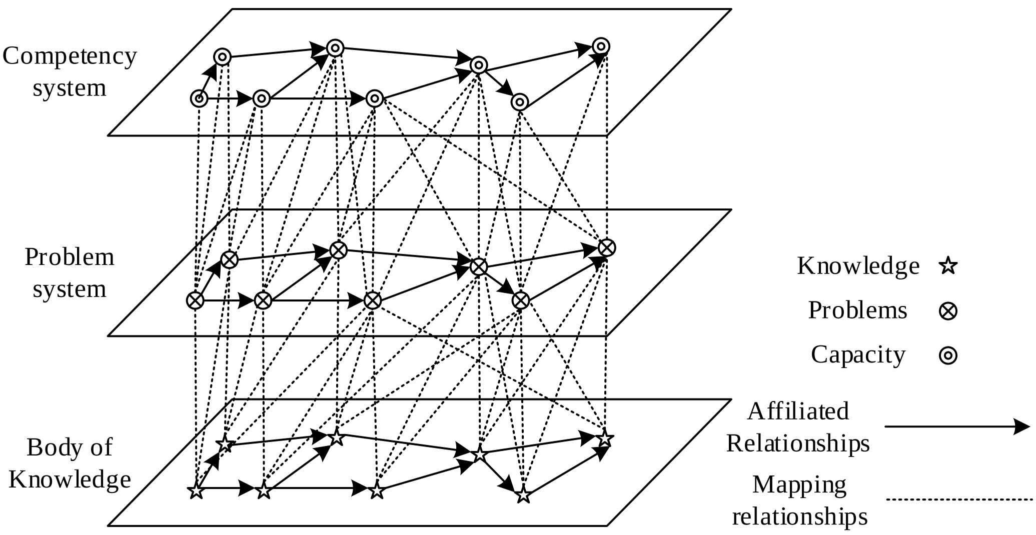


Figure 1. E-GPPE-C model of subject knowledge map

The capability system is formally expressed as:

$$A = \{A_1, A_2, \ldots A_n\} \tag{1}$$

The problem system is expressed as:

$$Q = \{Q_1(A_i), Q_2(A_i), \ldots Q_n(A_i)\} \tag{2}$$

The body of knowledge is formally expressed as:

$$K = \{K_1(K_j), K_2(K_j), \ldots K_2(K_j)\} \tag{3}$$

Disciplinary knowledge mapping is formally expressed as:

$$\{A_1, A_2, \ldots, A_n\} \cup \{Q_1(A_i), Q_2(A_i), \ldots Q_2(A_i)\} \cup \{K_1(K_j), K_2(K_j), \ldots K_2(K_j)\} \tag{4}$$

2.2 Disciplinary Knowledge Mapping

The core of the operation of the E-GPPE-C model of smart teaching lies in the dynamic collection of learning data based on subject knowledge mapping, the portrayal of learner learning, the precise regulation of the learning process, the provision of appropriate learning content and ways for learners to carry out learning activities, and the provision of the most suitable teacher guidance and peer help for learners to promote their smart development [24]. Therefore, the implementation of smart teaching cannot be separated from the support of learner profiling and learning services, and the recommendation of personalized learning services includes the recommendation of personalized learning paths and the construction of learning communities.

2.2.1 Learner Profile Construction

Computational modeling based on learning outcome data is a mapping of learners' mastery status of subject knowledge, problems, and competencies based on subject knowledge mapping [25]. The computational modeling of learner portrait based on learning outcome data in this study is based on subject knowledge mapping, i.e., the computational analysis of learning outcomes reflects the degree of learner knowledge learning, problem-solving, and competency formation, with the degree (D) taking a value between 0 and 1. If the value is larger, the higher the degree of mastery; conversely, if the value is smaller, the lower the degree of mastery. Learning outcome computational modeling is the process of mapping the learner's mastery state of subject knowledge, problems, and competencies based on subject knowledge mapping [26]. The learning outcome portrait should include the degree of formation of disciplinary competence, disciplinary problems and disciplinary knowledge, with D indicating the degree and level of learning.

It is known that a monitoring data matrix $Y = (y_1, y_2, y_3, ..., y_N)$, Y is $N*J$ -dimensional, N means that there are N students, J means that there are J questions. Find the initial values of each parameter K_{S0}, M_{r0}, T_{d0}, T_{t0}, T_{C0} and compute them:

$$Ll_0 = \sum_{k=1}^{K} f(K_{S0}, M_{r0}, T_{d0}, T_{t0}, T_{C0}) \tag{5}$$

Combining confidence level r and degree d, Ll is calculated as:

$$Ll = L(Ll_0, r, d) \tag{6}$$

Calculate the similarity sim between Ll and subject knowledge map KG as:

$$sim(Ll, KG) = (\sum_{i=1}^{n} |Ll_i - KG_i|^p)^{1/p} \tag{7}$$

If $sim >$ threshold, output knowledge mastery KD problem mastery QD, ability mastery AD. Combined with learner personality traits, output learner profile PKS, calculated as:

$$\begin{aligned} PKS &= \sum (KD_i, QD_i, AD_i) \\ &= (KD_1, KD_2, ..., KD_i) \cup (QD_1, QD_2, ..., QD_i) \cup (AD_1, AD_2, ..., AD_i) \end{aligned} \tag{8}$$

2.2.2 Learning path recommendation

The learning path is the "action guide" for smart teaching, and learning path recommendation is the key to realizing smart teaching. Therefore, the E-GPPEC model proposed in this study is based on subject knowledge mapping and learner profiles to carry out learning path recommendation, introduces learner behavioral data into the learning path recommendation, and takes into full consideration the intrinsic dependency relationship between the cognitive structure of learners and their knowledge in order to improve the accuracy and appropriateness of the learning path recommendation [27].

In this study, based on the planned group learning paths, the basic structure of the neural network for personalized learning paths is trained to generate personalized learning paths using an improved convolutional neural network (CNN). The specific steps are as follows:

1) The input layer is the group learning path in this study.

2) The function of the convolutional layer is to extract features from the input data, and the convolutional kernel is calculated as:

$$\begin{aligned} Z^{l+1}(i,j) &= [Z^l \times w^{l+1}](i,j) + b \\ &= \sum_{k=1}^{K_l} \sum_{x=1}^{f} \sum_{y=1}^{f} [Z_k^l(s_0 i + x, x_0 j + y) w_k^{l+1}(x,y)] + b \end{aligned} \tag{9}$$

where b is the deviation, Z^l and Z^{l+1} denote the convolutional input and output of layer $l+1$. $Z(i,j)$ corresponds to the pixels of the feature map, K is the number of channels of the feature map, and f, s_0, and p are the parameters of the convolutional layer corresponding to the convolutional kernel size, convolutional step size, and the number of filler layers.

3) The normalization layer is after the convolutional layer, and the inputs of the previous layer are normalized before entering the next layer, which can speed up the network training, effectively and prevent the gradient from disappearing. Its calculation formula is:

$$\rho = \frac{1}{n} \sum_{i=1}^{n} X_i \tag{10}$$

$$\sigma^2 = \frac{1}{n} \sum_{i=1}^{n} (X_i - \rho)^2 \tag{11}$$

$$Y_i = \frac{x_i - \tau}{\sqrt{\sigma^2 + \mu}} \tag{12}$$

$$Y_i' = \alpha Y_i + \beta \tag{13}$$

Where, ρ represents the mean, X represents the original data, n represents the number of samples, σ^2 is the variance, μ represents the constant, and α & β are the learning parameters.

4) The function of the pooling layer is to convert the results of individual points in the feature map into statistics of their neighboring regions. In this study, Lp pooling model is used and its basic representation is:

$$A_K^l(i,j) = \left[\sum_{x=1}^{f} \sum_{y=1}^{f} A_K^l(s_0 i + x, x_0 j + y)^p \right]^{1/p} \tag{14}$$

5) The fully connected layer is located at the end of the hidden layer of the convolutional neural network and passes signals to the other fully connected layers.

6) The output layer uses a classical logistic regression model to generate personalized learning paths.

2.2.3 Learning community building

Learning community construction is to combine group learners in homogeneous or heterogeneous combinations according to certain characteristics so that the learning community achieves the characteristics of intra-group heterogeneity and inter-group homogeneity. Learning styles can directly affect learners' emotions and behaviors and have a significant impact on independent learning, collaborative inquiry, and cooperative communication [28]. Therefore, clustering construction based on learning styles has become the mainstream way of building learning communities. This study utilizes pattern recognition technology to identify different learner characteristics, and based on the learning style data in the learner portrait, a clustering algorithm is used to automatically construct a learning community, which mainly consists of dividing the clusters, initially constructing the learning community and hierarchical clustering. Here are the specific steps:

1) Classification clustering

The mean shift clustering algorithm is used to preliminarily divide the group learners into clusters, and its calculation formula is:

$$M_h(x)=\frac{\sum_{i=1}^{n} G\left(\left\|\frac{x_i-x}{h}\right\|^2\right) w(x_i)(x_i-x)}{\sum_{i=1}^{n} G\left(\left\|\frac{x_i-x}{h}\right\|^2\right) w(x_i)} \tag{15}$$

2) Constructing a learning community

Based on the similarity of learners' learning styles, the AGNES hierarchical clustering algorithm is used in this study, in which individual samples in the dataset are regarded as initial clustering clusters. In each step of the algorithm, the two closest clusters are identified to be merged and repeated until the preset number of clusters is reached [29]. A heterogeneous member is merged for each learning community in turn until all learners are merged to complete the construction of the learning community, which is calculated as:

$$d_{avg}(C_i,C_j)=\frac{1}{|C_i||C_j|}\sum_{x\in C_i}\sum_{Z\in C_i} dist(x,z) \tag{16}$$

where C_i and C_j denote the two clusters that need to be combined for computation.

3 Validation and establishment of smart teaching models

To validate the E-GPPE-C model of wisdom teaching proposed in Chapter 2 and to test the role of environmental factors in influencing students' levels of wisdom. This chapter will be based on the empirical study of the causal generation and moderating and facilitating roles and specific path relationships between the three levels of elements of the E-GPPE-C model of wisdom teaching based on the use of the structural equation modeling method [30].

3.1 Assumptions about the relationships of key elements of smart teaching and learning

3.1.1 Causation and Moderation Setting

In a certain sense, among the activity layer elements of wisdom teaching in this study, problem creation, context creation, and inspired evaluation adjustments are the cause of the development of students' wisdom elements, and wisdom development is the effect of the change in the activity elements [31]. Therefore, according to the causal relationship between the activity layer elements of the E-GPPE-C model of wisdom teaching and the wisdom elements of the purpose layer, it is determined that the activity layer elements of the wisdom classroom as problem creation, context creation, and inspirational evaluation are exogenous latent variables, and the wisdom elements of the purpose layer as instrumental thinking, value thinking, and meaning thinking are endogenous latent variables. In view of the facilitating moderating effect of AI technology support elements on the causal relationship between the activity layer elements and the purpose layer wisdom elements of the E-GPPE-C model of wisdom teaching, it was identified as a moderating variable.

1) Formulation of the causal relationship hypothesis

As far as the causal relationship between the elements of smart teaching activities and the elements of purpose is concerned, this study proposes hypotheses based on the E-GPPE-C model of smart teaching about the structural relationship of the elements [32]:

H1 is that problem creation has a significant positive effect on students' instrumental thinking.

H2 is that problem creation has a significant positive effect on students' value thinking.

H3 is that problem creation has a significant positive effect on students' meaning thinking.

H4 is that context creation has a significant positive effect on students' instrumental thinking.

H5 is the significant positive effect of context creation on students' value thinking.

H6 is the significant positive effect of inspired evaluation on students' value thinking.

H7 is that inspired evaluation has a significant positive effect on students' meaningful thinking.

2) Formulation of the hypotheses of moderating relationships

This study argues that AI technology support has a moderating effect on each of the seven hypotheses regarding the generation of a causal influence relationship between the activity element and the purpose element. Therefore, as far as the moderating effect of technology elements is concerned, seven moderating relationships should also exist. As a result, seven hypotheses were formulated:

H8 is that AI technology support has a significant moderating effect on the path of "problem creation - tool thinking".

H9 is that AI technology supports a significant moderating effect on the path of "problem creation-value thinking".

H10 is the significant moderating effect of AI technology on the path of "problem creation-meaningful thinking".

H11 is the significant moderating effect of AI technology on the pathway of "situation creation - instrumental thinking".

H12 is the significant moderating effect of AI technology on the pathway of "situation creation-value thinking".

H13 is the significant moderating effect of AI technology on the pathway of "Inspiration and Evaluation - Value Thinking".

H14 is the significant moderating effect of AI technology on the pathway of "Inspiring Evaluation - Meaningful Thinking".

3.1.2 Hypothetical modeling

Based on the above assumptions, the hypothetical model of the relationship between the key elements of smart teaching and learning set in this paper oriented to the testing of the E-GPPE-C model of smart teaching is shown in Figure 2, which is based on the identification of exogenous latent variables, endogenous latent variables, observed variables reflecting each latent variable and the relationship between each latent variable. In this study, the hypothesized model oriented to the E-GPPE-C model test of wise teaching was proposed, including seven latent variables and 24 observed variables, as well as six causal hypotheses and six moderating hypotheses.

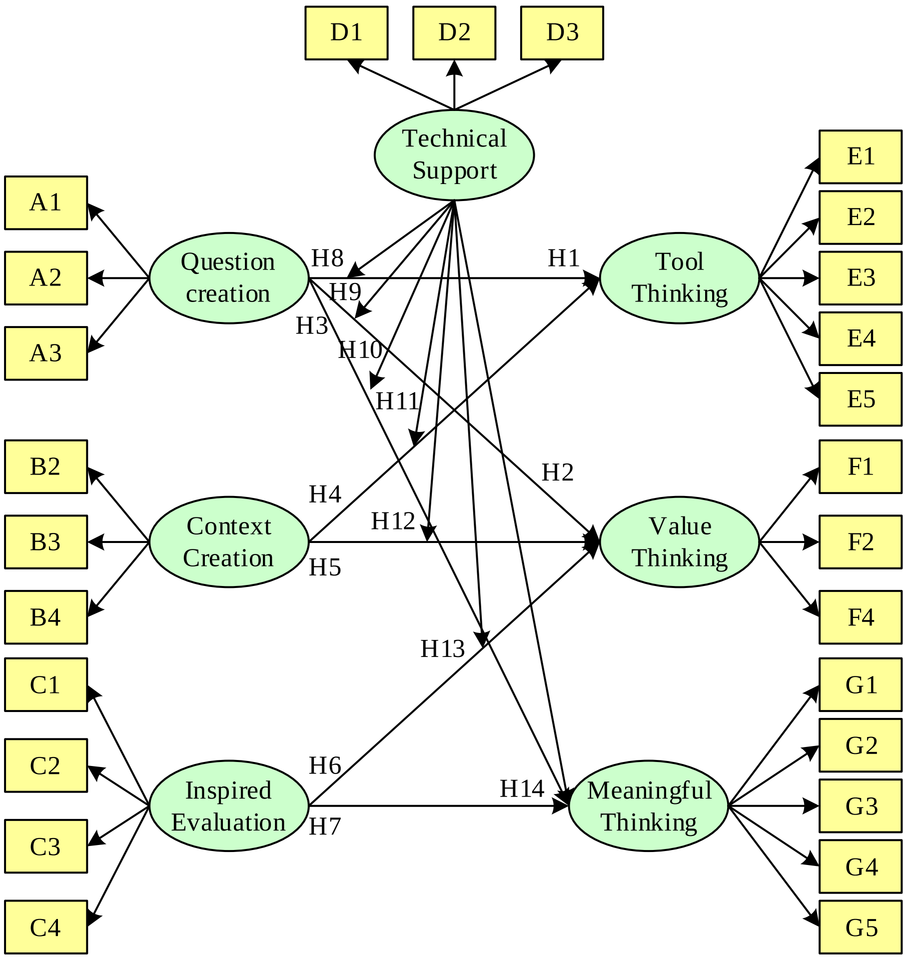


Figure 2. E-oriented GPPE -C test the wisdom of teaching key elements of relationship

3.2 Tests of the measurement model

3.2.1 Measurement model overall fitness test

The results of the fitness test of the measurement model constructed in this study using the great likelihood method based mainly on Hair's point of view are shown in Table 1. Among them, the chi-square value of the measurement model χ^2 =584.500, P=0.000. Degree of freedom *df*=289.15, MSEA=0.067 (<0.08), χ^2 /*df*=2.4482 (<3), GFI=0.911 (>0.9), NFI=0.923 (>0.9). In addition, all other indicators meet the fitness criteria. A comprehensive examination of the values of the indicators reveals that the overall fitness of the measurement model constructed in this study is good and, in general, does not require any further correction.

Table 1. Measures the fit parameters of the model

Statistical	Absolute adaptation index			Value added fit index			Simple adaptation degree index		
	χ^2/df	RMSEA	GFI	NFI	IFI	CFI	PNFI	PCFI	P GFI
Standard	<3	<0.008	>0.9	>0.9	>0.9	>0.9	>0.5	>0.5	>0.5
Actual value	2.4482	0.051	0.911	0.923	0.947	0.938	0.756	0.781	0.723
Other parameters: sample = 103, Chi-square value χ^2 =584.500, P=0.000, Degrees of freedom df = 289.15.									

3.2.2 Measurement model intrinsic structural fitness assessment

As far as the assessment of structural reliability is concerned, this study chose to observe the two values of the Clonbach coefficient α and the combined reliability ρ as the basic basis. If the α coefficient is above 0.7, it is considered acceptable. Combined reliability ρ is greater than 0.6, then the model quality can be considered ideal. The higher the combined confidence ρ, the higher the internal consistency of the conformation.

The formulae for both Cronbach's coefficient α and combined confidence ρ are:

$$\rho = \frac{\left(\sum_{i=1}^{p} \lambda_{yi}\right)^2}{\left(\sum_{i=1}^{p} \lambda_{yi}\right)^2 + \sum_{i=1}^{p} Var(\varepsilon_i)} \tag{17}$$

$$\alpha = \left(\frac{N}{N-1}\right) * \left(1 - \frac{\sum_{i=1}^{N} \sigma_i^2}{\sigma_i^2}\right) \tag{18}$$

Based on the above analysis, this study uses the method of great likelihood (ML) to estimate the parameters of the indicator reliability and structural reliability of the measurement model, and the calculation results are shown in Table 2. It can be seen that, as far as the index reliability of the measurement model is concerned, the factor loadings λ of each measurement item are greater than the judgment standard of 0.4. In terms of the structural reliability of the measurement model, the combination reliability ρ and Cronbach's coefficient α are greater than the judgment standard of 0.7. Thus, in a certain sense, it can be concluded that the measurement model of this study has good reliability.

Table 2. Reliability assessment of the measurement model

Parameters	Title	The significant parameters estimation			The index of reliability		Structure	α
		Unstd	S.E	Z-value	λ	λ^2	CR (ρ)	
Problem creation	A1	1.000			0.770	0.455	0.786	0.743
	A2	0.882	0.067	18.160	0.717	0.352		
	A3	0.670	0.071	15.138	0.779	0.436		
Situation creation	B1	1.000			0.604	0.651	0.814	0.833
	B2	0.786	0.054	17.428	0.738	0.617		
	B3	1.066	0.064	15.227	0.771	0.425		
Enlighten reviews	C1	1.000			0.794	0.657	0.793	0.806
	C2	1.065	0.054	18.837	0.741	0.411		
	C3	1.098	0.076	16.955	0.616	0.417		
Technical support	D1	1.000			0.584	0.545	0.744	0.787
	D2	0.915	0.071	16.761	0.814	0.709		
	D3	0.987	0.076	18.241	0.574	0.694		
Instrumental thinking	E1	1.000			0.846	0.709	0.852	0.868
	E2	1.035	0.053	14.270	0.687	0.568		
	E3	0.691	0.055	18.574	0.630	0.507		
	E4	0.999	0.075	18.834	0.698	0.719		
Value Thinking	F1	1.000			0.529	0.697	0.825	0.839
	F2	1.055	0.055	18.351	0.787	0.596		
	F3	0.871	0.080	18.892	0.840	0.337		
Meaning Thinking	G1	1.000			0.696	0.682	0.861	0.833
	G2	0.633	0.054	19.264	0.662	0.574		
	G3	0.870	0.072	16.701	0.779	0.616		
	G4	0.971	0.057	16.749	0.820	0.361		

4 Analysis of empirical results of smart teaching models

4.1 Analysis of the test results of the smart teaching model

This study was conducted with 103 students who attended classes at Smart Teaching, two classes per week, and were tracked for one cycle through a longitudinal experience sampling method. In order to maximize the information from the tracking data, the data from students who participated in two and three experience sampling surveys were selected for analysis in this study, and a total of 95 subjects were finally included in the data analysis. The relationship between situational awareness and learning engagement was separately analyzed through the steps of prerequisite validation and cross-lag modeling with random intercepts. Autoregression is commonly employed to maintain the stability of the time series due to the traditional cross-lag modeling. In this approach, both variables vary around the same sample mean, and there are no intraindividual differences at the trait level.

4.1.1 Descriptive statistical analysis

Based on the results of the longitudinal validity validation of the model, in the subsequent analysis, contextual perception from the smart teaching model included two dimensions: media technology perception and social interaction perception. The learning input dimension includes three dimensions: behavioral input, deep cognitive input, and emotional input.

This study first descriptively analyzed the results of the variables related to contextual perception and learning input, as shown in Table 3. In particular, T1, T2, and T3 denote the three-time points of experience sampling, and T1-T3 denote the mean and standard deviation of the overall data at these three time points. Finally, the two columns represent the results of the one-way ANOVA test for the three measurements. As can be seen from the mean values of the factors, the mean values of contextual perception ranged from 4.05-4.33, and the mean values of media technology perception ranged from 4.31-4.38, tending to be between slightly conforming and conforming. The mean value of social interaction perception is between 3.93-4.24, which means that it tends to be slightly non-conforming to conforming. The mean values of the scores of contextual perception and all dimensions are above 3.90, which indicates that students' contextual perception is relatively positive on the whole in the smart teaching and learning environment. In terms of the trend of change, students' situational awareness showed a gradual increase from the second week. However, as shown by the results of the one-way ANOVA, this upward trend did not reach a significant difference.

Table 3. Descriptive analysis results

Dimensionality	T1	T2	T3	T1-T3	F	Sig.
Situational awareness	4.05 ± 0.81	4.16 ± 0.72	4.33 ± 0.94	4.18 ± 0.81	0.921	0.407
Media technology awareness	3.93 ± 0.77	4.09 ± 0.64	4.24 ± 0.90	4.11 ± 0.54	0.104	0.911
Social interaction perception	3.87 ± 1.12	3.98 ± 0.85	4.12 ± 1.06	4.01 ± 1.01	1.633	0.108
Learning	4.41 ± 0.89	4.58 ± 0.74	4.66 ± 0.98	4.55 ± 0.99	1.636	0.213
Behavior	4.27 ± 1.12	4.39 ± 0.79	4.50 ± 0.93	4.40 ± 0.83	1.837	0.161
Cognitive input	4.52 ± 0.96	4.64 ± 0.88	4.67 ± 0.92	4.61 ± 0.74	1.248	0.299
Emotional engagement	4.29 ± 1.06	4.38 ± 0.95	4.46 ± 0.91	4.38 ± 0.90	2.235	0.007

4.1.2 Relationship between perceived instructional context and behavioral engagement

In the study of the stability of instructional contextual perceptions and behavioral inputs, the intertemporal correlation coefficients of instructional contextual perceptions for the three measurements are shown in Table 4. The correlation coefficients of teaching contextual perceptions ranged from 0.653-0.755, and all of them were significantly correlated. The intertemporal correlation coefficients of behavioral inputs are between 0.221-0.486, all significantly correlated, so the teaching context perception and learning inputs are all somewhat stable and satisfy the stability condition. The synchronous correlation coefficients of teaching contextual perception and behavioral input at the same time points are mainly between 0.238-0.372, and all of them are significantly correlated except for two that are not significant. Therefore, teaching context perception and behavioral input basically satisfy the correlation and synchronization conditions.

Table 4. The relationship between situational perception and behavioral engagement in teaching

Teaching situational awareness				
The sequential	Factor	1	2	3
1	T1 Teaching situational awareness	1.000		
2	T2 Teaching situational awareness	0.775**	1.000	
3	T3 Teaching situational awareness	0.653**	0.684**	1.000
Behavior				
1	T1 Behavior	1.000		
2	T2 Behavior	0.486**	1.000	
3	T3 Behavior	0.258*	0.221*	1.000
Teaching situational awareness & Behavior				
The sequential	Factor	T1 Behavior	T2 Behavior	T3 Behavior
1	T1 Teaching situational awareness	0.238*	0.256	0.274
2	T2 Teaching situational awareness	0.305**	0.366**	0.252
3	T1 Teaching situational awareness	0.245*	0.247*	0.372**

It was verified that the two variables of teaching contextual perception and behavioral input meet the conditions for setting up a cross-lagged model, and this study set up a cross-lagged model of teaching contextual perception and behavioral input. In the model set, the mean value of situational perception and the mean value of behavioral input are regarded as latent variables, and the two variables at the same time point are correlated, while no correlation is allowed between the error terms between the variables at other time points. The final analytical results of the cross-lagged model of situational awareness and behavioral inputs are obtained, as shown in Figure 3, where PERC is situational awareness and BEH is behavioral inputs. It can be seen that $\chi^2 / df = 0.115$, CFI=1.000, TLI=1.123, RMSEAS=0.002, SRMR=0.007, and the model results are well-fitted. Behavioral inputs of T1 can positively predict the teaching context perception of T2, and behavioral inputs of T2 can positively predict the teaching context perception of T3. That is, students' behavioral input is the antecedent variable of teaching context perception, and the more positive students' behavioral input in the smart teaching environment, the better their subsequent teaching context perception. Since the coefficients of the two cross-lagged paths were significant, the effect of behavioral input on the perception of teaching context may be stable.

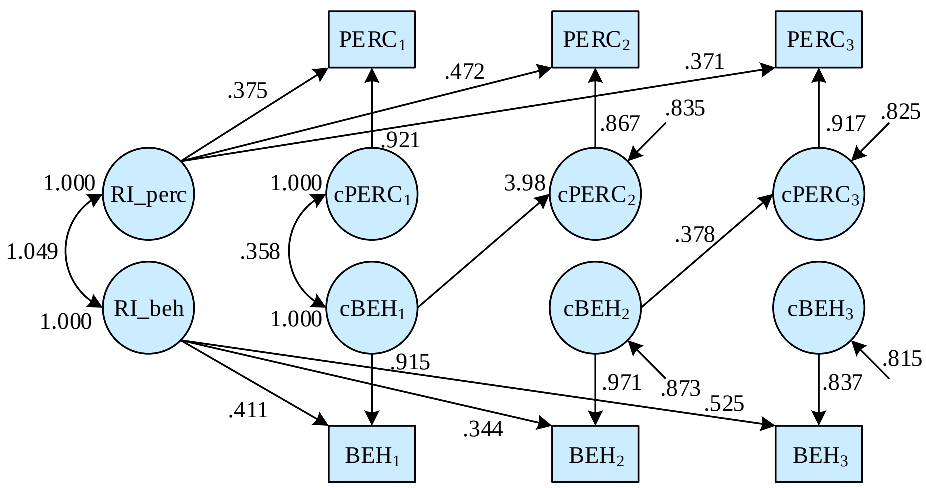
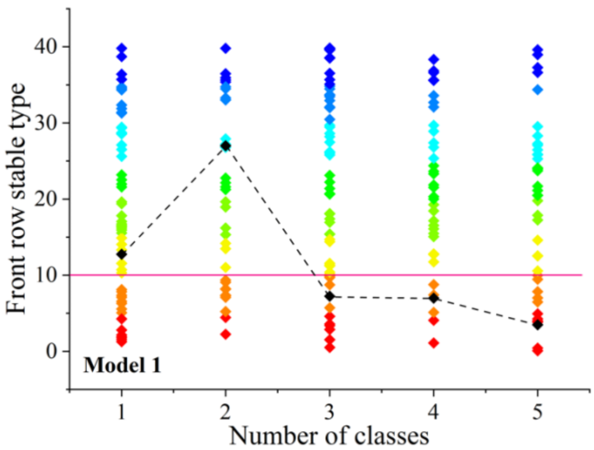


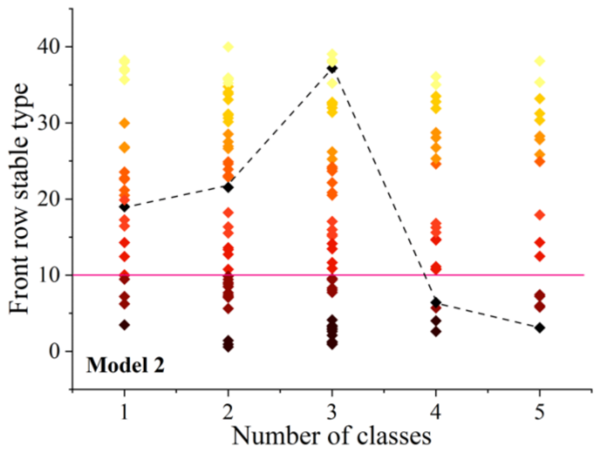
Figure 3. Cross-lag model of situational perception and behavioral engagement

4.2 Exploration of Timing Influences

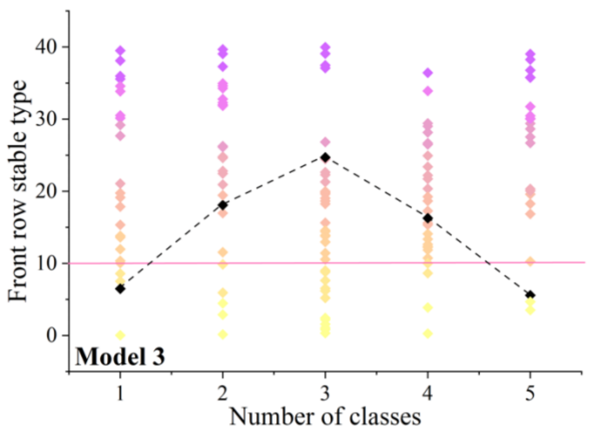
In this study, 45 students who participated in the course of Advanced Mathematics, a compulsory course in higher education, were selected. The vertical coordinate is the specific seat number and the horizontal coordinate is the number of sampling times for empirical sampling to establish a right-angled coordinate system. The location trends of the students in the course for five sampling times are shown in Fig. 4. Among them, Fig. 4 (a), (b), (c) and (d) show the trends of model 1~4 changes, respectively. As can be seen from the figure, the students basically did not sit in their previous seats in each class. There are a few students who change steadily between the front row and the back row, but a large part of the students change between the front row and the back row. The analysis of the factors influencing the actual location of the second time is mainly a logistic regression of the first experience sampling data on the second experience sampling data. They were distance from the podium, distance from the screen, distance from the center point, and facing front and back, respectively. Then, layer-by-layer binomial logistic regression was conducted with distance from the podium, distance from the screen, distance from the center point, and facing forward and backward as the dependent variables to obtain Model 1, Model 2, Model 3, and Model 4, respectively. The first layer was course type, achievement expectation, self-efficacy, autonomous motivation, controlled motivation, and location preference. The second layer is T1 technical media perception, T1 social interaction perception, T1 behavioral input, T1 deep cognitive input, and T1 affective input, where T1 denotes first experience sampling.



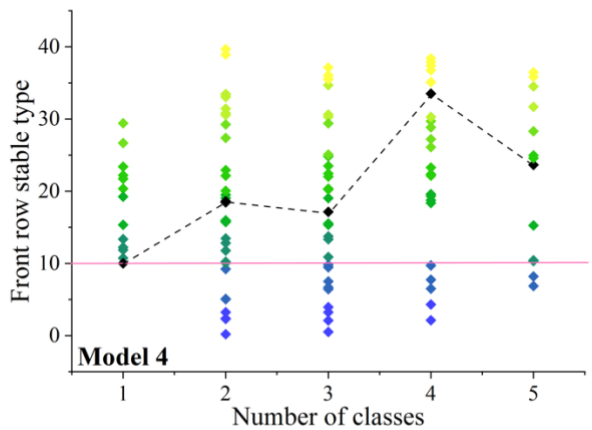
(a) Trends in Model 1



(b) Trends in Model 2



(c) Trends in Model 3



(d) Trends in Model 4

Figure 4. Position changes

The results of the statistical test measure indicator-2 loglikelihood, Cox & Snell's R^2, and Nagelkerke's R^2 for Models 1-4 are shown in Table 5.The sig. The value of Hosmer & Lemeshow's test represents whether or not the difference between the predicted values and the actual observations is significant. If the sig. Is less than the significance level of 0.05, then it represents that the predicted values are significantly different from the observed values and the model is not well fitted. If sig. is greater than the significance level of 0.05, it means that there is no significant difference between the predicted values and the observed values, and the model fit is good. It can be seen that Sig.=0.923>0.05 for model 1, Sig.=0.674>0.05 for model 2, Sig.=0.705>0.05 for model 3, and Sig.=0.621>0.05 for model 4 have a better fit. It can be seen that the conclusions obtained from the analysis of the data of models 1-4 are valid and reliable.

Table 5. Overall evaluation of each model

	Step	Model 1	Mode 2	Mode 3	Mode 4
-2 loglikelihood	1	114.31 ^{a}	81.33 ^{a}	105.37 ^{a}	114.87 ^{a}
Cox & Snell R^2	1	0.175	0.184	0.191	0.157
Nagelkerke R^2	1	0.218	0.293	0.270	0.215
Chi-square	1	3.135	5.782	5.141	6.358
df	1	10	10	10	10
Sig.	1	0.923	0.674	0.705	0.621

4.3 Analysis of the Influence Mechanisms of Smart Teaching

From the previous section, it can be seen that smart teaching successfully triggered significant changes in students' engagement, learning strategies and creativity levels. In this section, the relationship between them will be further explored through multiple regression analysis in order to delve deeper into the mechanism of influence of smart teaching. Since the CDWR scales used to assess creativity levels are different from those of other instruments, they need to be standardized by converting them into Z-scores before the multiple regression analysis. After standardization, the Durbin-Watson test showed that the residuals were uncorrelated with each other, and there was no correlation problem d =2.008. Variance inflation factors of $VIF \in \{1.411, 1.354, 1.337, 1.215, 1.616\}$, were less than 10, indicating that there was no problem of multicollinearity between the respective variables.

The results of the regression of the coefficients of the respective variables of the Smart Teaching Model are shown in Table 6, and it can be found that they all explain the changes in the level of creativity. Specifically, prior creative experience explains the change in creativity the most strongly β=0.424, p=0.001. Followed by the deep learning strategy in order of magnitude β=0.286, p =0.031, which indicates precisely the specific mechanism of action by which wise teaching influences the eventual ability of students to learn.

Table 6. Regression results of variable coefficients of intelligent teaching models

Variable	Not standardized coefficient		Standardized coefficient β	t	Sig.
	B	Standard error			
Constant	0.041	0.114	—	0.332	0.752
Previous experience to create	0.473	0.131	0.424	3.275	0.001
Wisdom classroom	0.253	0.108	0.211	2.289	0.032
Class participation,	0.246	0.137	0.203	2.031	0.042
Flow level	0.244	0.115	0.254	2.113	0.037
Deep learning	0.281	0.129	0.286	2.287	0.031

5 Conclusion

Based on the smart learning E-GPPE-C model and subject knowledge mapping, this study proposes a learner portrait portrayal and personalized learning service recommendation method for the realization of the smart learning system. After in-depth research and practice, the main conclusions of this study are as follows:

1) The smart teaching model consists of three levels, i.e., physical layer, activity layer, and purpose layer, and seven elements, i.e., technical support, problem creation, context creation, inspiration and evaluation, instrumental thinking, value thinking, and meaningful thinking.

2) The intertemporal correlation coefficients of the behavioral inputs under the smart teaching model range from 0.221-0.486, all of which are significantly correlated so that the perception of the teaching context and the learning inputs have a certain degree of stability and satisfy the stability condition.

3) The E-GPPE-C model of smart learning includes six core elements: learning environment, subject knowledge mapping, learner portrait, learning path, learning evaluation, and learning community, and the model consists of five layers from the bottom to the top: the foundation layer, the support layer, the service layer, the key layer, and the application layer. The development of smart learning is supported by the interconnection of the five layers of the model. The operation mechanism of the model includes a monitoring mechanism, control mechanism and optimization mechanism, and the three groups of operation mechanisms are interconnected to form a closed loop of intelligent learning model operation, which jointly promotes the intelligent learning of learners.

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