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Theoretical Model Construction and Path Exploration of Intelligent Party Building Education in Colleges and Universities

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Abstract

In the digital transformation era, higher education stands on the cusp of a revolution. This paper dives into the heart of this transformation, presenting a novel model of intelligent party building education that leverages digital technology to forge a new path for learning. Through the lens of ecological construction, we unveil the CFA model and a sophisticated deep knowledge tracking method aimed at enhancing student performance in Civic and Political Sciences. Our journey through empirical analysis and comparative experiments sheds light on the transformative power of digital education techniques. Despite the initial findings suggesting a modest impact of smart party building and teaching methods on knowledge retention (with significance levels of 0.6941 and 0.4963), a deeper exploration reveals a compelling narrative: the synergistic effect of these methods significantly boosts knowledge retention, as demonstrated by an F-value of 5.6941 and a P-value below 0.05. The prowess of Civics teachers, assessed across three dimensions, further narrates the success of this educational innovation, with scores reflecting their deep understanding of the curriculum and a robust theoretical knowledge base. The performance of 32 Civics teachers, with scores ranging from 12 to 24, underscores the efficacy of intelligent party building education in today's colleges and universities.

Keywords: CFA model; Deep knowledge tracking; Crossover effect; Intelligent party building education.

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1 Introduction

Education changes and develops with the advancement of technology. From mechanization, automation, and computerization to informatization, there has been a major shift in educational concepts, goals, contents, and methods [1-2]. The rapid development of informatization to digitalization has given rise to smart education that optimizes the teaching process and promotes learner development through human-computer collaboration [3-4]. Intelligent education, including interconnected learning scenarios, flexible and diversified learning modes, and elastic organization and management, is a new form of education in the digital era [5].

At the beginning of 2022, China launched the implementation of the national education digitalization strategy action, built the national smart education public service platform, aggregated 45,000 basic education curriculum resources, 6,758 vocational education quality courses, 28,000 higher education quality catechism and experimental courses, expanded the coverage of high-quality education resources, and effectively promoted the balanced development of education [6-8]. Based on its advantages of openness, sharing, interactivity, collaboration, digitalization, networking, and intelligence, smart education has a positive role in meeting students' individualized learning needs, improving teachers' teaching ability and teaching quality, and realizing all-area, high-quality, and balanced education [9-11].

In May 2023, when presiding over the fifth collective study of the Political Bureau of the Central Committee of the Communist Party of China (CPC), General Secretary Xi Jinping emphasized the need to "further promote digital education to provide effective support for personalized learning, lifelong learning, expanding the coverage of high-quality educational resources, and modernization of education" [12-15]. The digital era is a brand new stage in the history of human social development. Sustainable development is the golden key to cracking global problems, and the sustainable development of higher education in the future will be better realized through digital transformation [16-18]. In the era of smart education, universities must innovate the concept of higher education, expand the connotation of higher education management, and improve the organizational structure of higher education management in order to respond effectively to the transformation and development of higher education [19-21].

The General Office of the Central Committee of the Communist Party of China issued the "2014-2018 National Party Education and Training Work Plan", which proposes that party building work according to the new situation and new tasks, the need to carry out innovative work concepts, content, situation, and methods [22-24]. Party-building in colleges and universities from the initial regular party learning and party activities into the era of wisdom party building combined with traditional media and the party organization's website, modern distance education, cell phone newspaper, microblogging, web, WeChat, and other information technology platforms for wisdom online learning and training [25-26]. Wisdom-era party-building work is no longer simply the construction of teaching models and teaching courses; it is teaching and media co-construction, democratic evaluation, and data mining support for the wisdom of the party-building era [27].

Starting from the theoretical model of intelligent party-building education in colleges and universities, this paper proposes an ecological model of intelligent party-building in colleges and universities, which contains four aspects: Reform of party-building curriculum, Reform of party building resources, Reform of party building management mode and Feedback of party building effect. Based on the importance of predicting students' Civic and Political scores in intelligent party-building education, the CFA model is constructed. The students' Civic and Political a priori scores are calculated using the score matrix and the corresponding deviation matrix. The multidimensional feature vectors of the Civic and Political scores are inputted into the multilayer perceptual machine to predict the predicted

Civic and Political scores of the students. The DKT model is modified by adding the correction module and student behavioral factor information, and the updated DKT-Correcting model is used to determine students' learning characteristics. The combined features of students' learning interaction information and behavioral features are inputted into the knowledge tracking board to calculate the interaction information vector. Construct experimental groups to analyze the effect of intelligent party-building education in colleges and universities on students' civics performance and teachers' classroom civics ability.

2 Theoretical Model Construction of Intelligent Party Building Education in Colleges and Universities

2.1 Smart Party Building Ecology Proposed

Modern party building is no longer simply the construction of teaching methods and teaching curricula. Instead, it is the era of intelligent party building supported by teaching, media co-construction, and democratic evaluation data mining. Figure 1 shows the Reform and construction of party-building ecology, and the modern intelligent party-building ecology is mainly explored in four aspects, namely, curriculum reform, party-building idea reform, communication mode reform, and democratic evaluation reform, to establish an intelligent party-building ecology based on information technology, driven by intelligent data as the core, and supported by communication media.

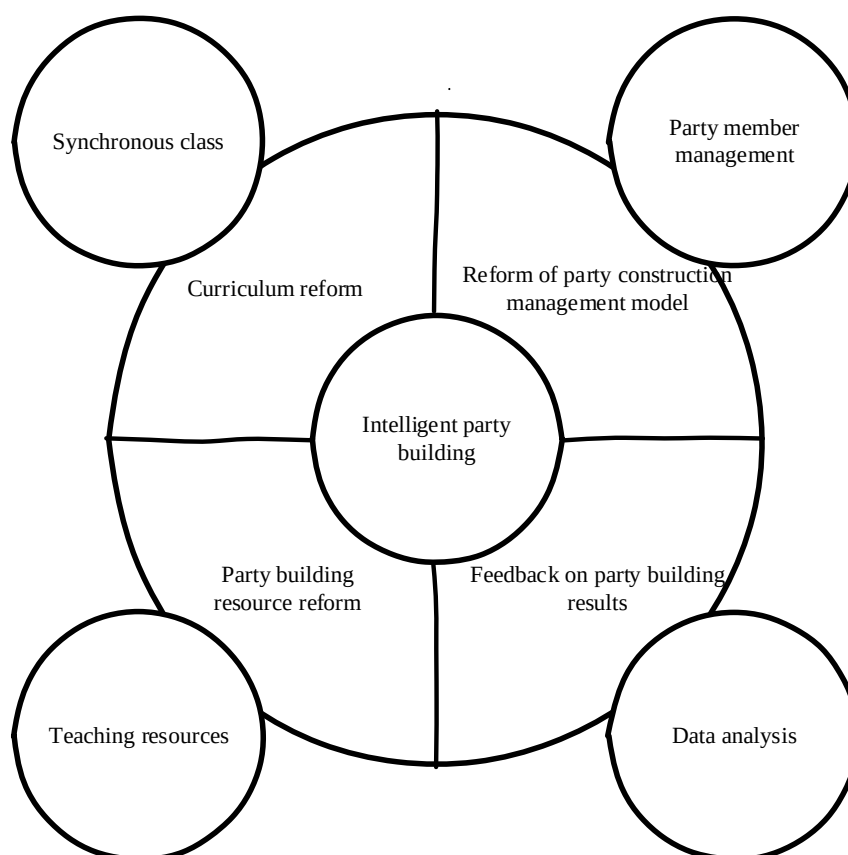


Figure 1. The Party building ecological Reform and construction

2.1.1 Reform of the party building curriculum

Combined with the theory of pedagogy, psychology, education technology, to explore the shortcomings of traditional party building education, online party building education, and gradually promote the Party building classroom in colleges and universities, course reform pilot mode, the course is divided into an introductory class, classified special class and seminar analysis class, the introductory class for all party members to focus on learning, the main focus of the macro level of the party building education course, divided into the main classroom and subclassroom, the use of the classroom live mode, completed The main classroom and sub-classroom are divided into the main classroom and sub-classroom, using the live classroom mode to complete the “main classroom professor + sub-classroom teaching assistant” to conduct the class together, the classified special class is for different types and levels of party members, and the seminar and analysis class is in the mode of small group discussion and analysis through the party building platform and party building resources to support in-depth discussion and analysis by the small group.

2.1.2 Reform of party building resources

Party members' careers from the development object, preparatory party members to the official party members, in accordance with the concept of “people-oriented,” sorting out each stage of the party building learning needs, to realize the “platform full-cycle” management, to help party members to learn and accumulate, to achieve the accumulation of career hours, from the party history to the latest developments in the party systematic learning, and open personal party building space to realize the accumulation of all personal party building learning materials. The platform helps party members accumulate learning, from the history of the Party to the latest development of the Party, and also opens a personal party-building space to realize the accumulation of all personal party-building learning materials.

2.1.3 Reform of the party management model

The status and influence of traditional media have been affected by the rise of new media and self-media. Party-building work used to be mostly done using traditional media to establish the ideological consensus of party members and the use of traditional media such as newspapers and television to establish communication mimesis. In the modern era, which is also the era of new media, it is necessary to utilize the power of new media communication to establish an anthropomorphic environment for party-building communication among the party members and to promote mutual culmination among the party members in order to achieve the best effect of party building.

2.1.4 Feedback on the effectiveness of party building

Through the Reform of democratic evaluation and the use of a new model of big data analysis, information is collected from a variety of perspectives, including democratic evaluation, the effect of party building and learning, and the development of public opinion, to verify the specific effectiveness of party building, which is no longer measured purely by the form of scoring of democratic evaluation by party members and the public, but by the public opinion data from the daily work and life to reflect the effect of actual party building, which is more conducive to the discovery of problems and is used to improve the work of party building. Implementation.

2.2 Prediction of Student Achievement for Smart Party Building

Student performance prediction is one of the important research directions in the smart party education scenario, which predicts students' future test scores by constructing a performance prediction model and inputting information such as students' background, learning situation, and historical scores into the model.

2.2.1 General structure of the CFA model

In this paper, a student grade prediction model CFA combining collaborative filtering and attention mechanism is proposed to address the problems in grade prediction task. The overall structure of the model is shown in Fig. 2. The model contains three modules, which are a priori grade calculation module, a weighted attribute calculation module, and a student grade prediction module. Among them, the inputs are student attributes x_i as well as historical grades s_i , and the output is student predicted grades y' .

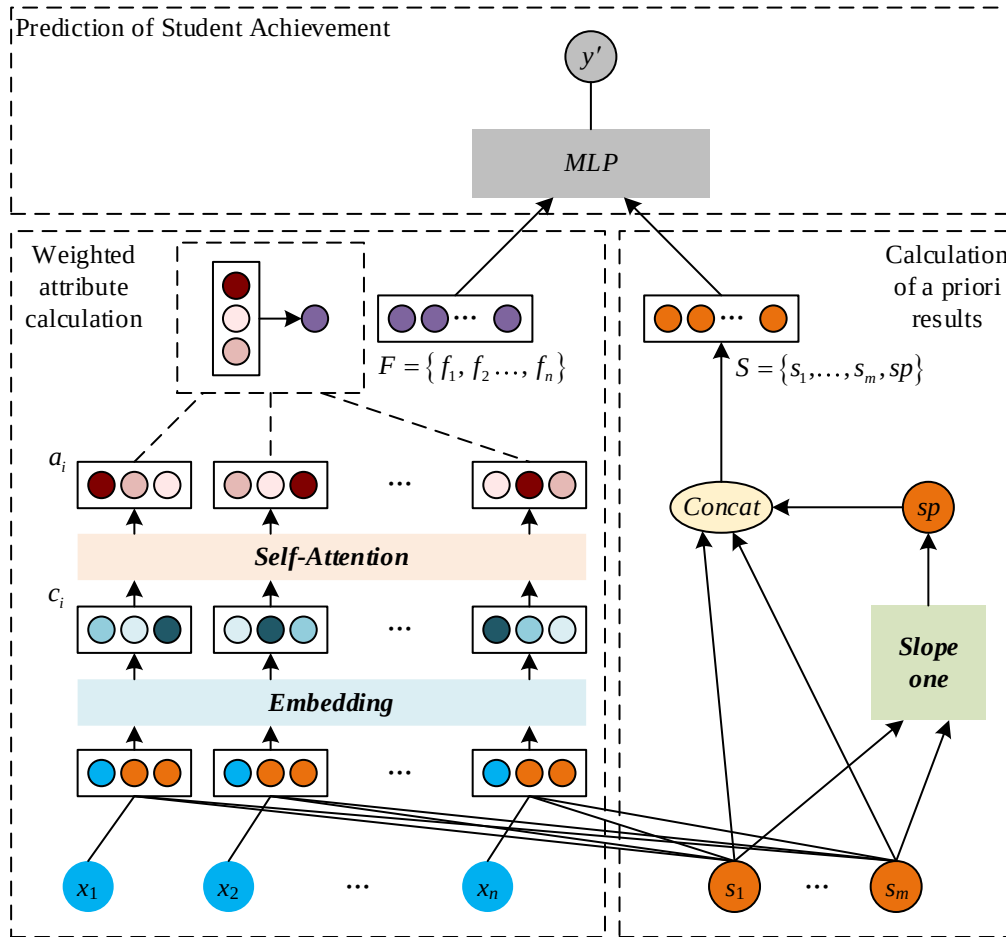


Figure 2. The general structure of the cfa model

2.2.2 Calculation of a priori results

Figure 3 shows the deviation matrix between the computed exams, where two students stu_1 and stu_2 and two exams sub_1 and sub_2 are given, student stu_1 scores 94 and 97 on exam sub_1 and

exam sub_2 , respectively, and student stu_2 scores 75 on exam sub_1 , where the difference in difficulty as well as the scope of the exams is relatively constant. Therefore, it is possible to predict Student stu_2 performance on Exam sub_2 from the deviation of Student stu_2 score on Exam sub_1 and Student stu_1 score on both exams. When there are multiple students and multiple exams, it is possible to construct the corresponding “student-exam” score matrix, which is necessarily a non-sparse matrix in the campus scenario. The score matrix can be used to construct the corresponding deviation matrix.

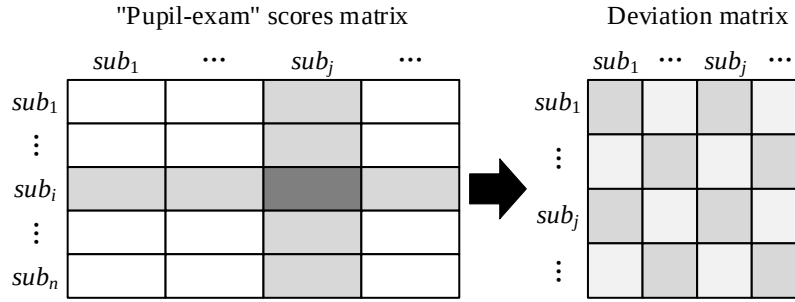


Figure 3. The deviation matrix between the calculation tests

The deviation matrix contains the average deviation of scores between two by two for all exams, and this average deviation is calculated as shown in Equation (1):

$$dev_{ij} = \frac{\sum_{k \in Stu_{ij}} s_k^i - s_k^j}{|Stu_{ij}|} \quad (1)$$

Where Stu_{ij} denotes the set of students with test scores on both exams sub_i and sub_j , $|Stu_{ij}|$ denotes the number of students in the set, s_k^i and s_k^j denote the historical scores of student stu_k on exams sub_i and sub_j , and the final dev_{ij} denotes the average deviation of scores on exams sub_i and sub_j . By repeating the above calculations, the deviation matrix of scores between all exams can be obtained. Once the deviation matrices are obtained, the students' a priori scores can be calculated using Equation (2):

$$sp_k^i = \frac{\sum_{j \in score_k} (s_k^j + dev_{ij})}{|score_k|} \quad (2)$$

Where sp_k^i denotes student stu_k a priori score prior to exam sub_i , $score_k$ denotes student stu_k collection of historical exams, $|score_k|$ denotes student u number of historical exams, s_k^j denotes student stu_k score on exam sub_i , and dev_{ij} denotes the mean score deviation between exams sub_i and sub_j .

The above steps are used to calculate the a priori scores of all students on the prediction test SP , and then the a priori scores are spliced with the students' historical scores SH to obtain the students' a priori knowledge characteristics S :

$$S = \text{concat}(SH, SP) \quad (3)$$

2.2.3 Prediction of student performance

In real situations, there is basically a non-linear relationship between student performance and student attributes, and the multilayer perceptron is one of the most widely used neural networks with powerful non-linear modeling capabilities.

The multidimensional feature vector x is input into the multilayer perceptual machine, and the output of each layer is used as the input of the next layer, and the result is finally obtained after layer-by-layer conduction, as shown in Equation (4):

$$\sigma(x_{L-1}) = \sigma(W_L x_{L-1} + b_L) \quad (4)$$

Where $W_L, x_{L-1}, b_L, \sigma$ denotes the weight matrix, input vector, bias term and activation function of layer L , respectively.

Here, the student's a priori knowledge feature S obtained from the a priori knowledge computation module and the weighted attribute F obtained from the weighted attribute computation module are concatenated and inputted into the multilayer perceptual machine to output the student's predicted score y' :

$$y' = \text{MLP}([F; S]) \quad (5)$$

2.3 Deep Knowledge Tracking Model

In this chapter, the DKT-Correcting model incorporates the correcting module and student behavioral factor information into the DKT model.

2.3.1 Behavioral Characterization Constructs

Learning behavior characteristics include students' behavioral data when answering questions, such as their answer time, whether they ask for help, etc. However, many scenarios, but not all datasets, contain students' behavioral data when answering questions; therefore, this section adds two student learning characteristics by means of computational statistics: the number of times a student answers correctly on the same exercises c_t , and learning efficiency s_t . The number of correct answers can reflect the improvement students get by doing the questions, but the characteristic is universal, while learning efficiency possesses the specificity of individual students:

$$c_t = \begin{cases} 0, & \text{Number of correct answers before the } t\text{th answer} = 0 \\ 1, & 1 \leq \text{number of correct answers before the } t\text{th answer} < 5 \\ 2, & \text{Number of correct answers before the } t\text{th answer} \geq 5 \end{cases} \quad (6)$$

Learning Efficiency s_t is the degree of absorption of knowledge by a student after practicing the same question several times, and is expressed in terms of the percentage of correct answers, which changes as the number of times the question is done increases and as the results of answering the question vary. The value of the correct answer rate is equal to the ratio of the number of correct

answers to the number of times the question was answered, when the student answered the exercise for the first time, the correct rate was set to 0.5. The correct answer rate was categorized to determine the student's learning efficiency level, and the following rule is displayed:

$$s_t = \begin{cases} 0, & 0 \leq \text{Correctness before the } t\text{th answer} < 0.33 \\ 1, & 0.33 \leq \text{Correctness before } t\text{th answer} < 0.67 \\ 2, & 0.67 \leq \text{Correctness before } t\text{th answer} \leq 1 \end{cases} \quad (7)$$

The crossover feature is calculated as shown in Equation (8):

$$C(q_t, s_t) = q_t + \max(q+1) * s_t \quad (8)$$

Where, q_t denotes the exercise number, $\max(q+1)$ denotes taking the maximum of the number plus one, and s_t denotes the learning efficiency of the student. After fusing the learning features and the exercise number into a single feature, the learning features are encoded by using solo thermal coding to obtain the corresponding learning feature vector. Repeat the method to encode all the learning features with solo thermal coding and finally splice them to get the learning behavior feature vector x_t^s :

$$x_t^s = \text{Onehot}(C(q_t, s_t)) \oplus \text{Onehot}(C(q_t, c_t)) \quad (9)$$

Forgetting characteristics are different from learning characteristics, forgetting characteristics will lead to the decline of students' overall knowledge level, and according to Ebbinghaus' forgetting curve theory analysis, forgetting factors are affected by the time interval and students' own forgetting characteristics. Therefore, two parameters are designed as forgetting factors in this section: the time interval from the last answer g_t , and the students' own forgetting degree f_t . The selection of forgetting factors is both universal and specific, with the degree of forgetting being specific and the other factor being universal.

The time interval from the last answer $g_t = (g_{1t}, g_{2t}, \dots, g_{it}, \dots), g_t$ has a dimension equal to the number of exercises, and g_{it} denotes the time interval between the t rd answer and the last answer to the i th exercise question. The student's own forgetfulness level f_t is constructed from the answer record, $f_t = (f_{1t}, f_{2t}, \dots, f_{it}, \dots), f_{it}$ denotes the student's answer error rate on the i th exercise question up to the t th answer and is calculated as shown in Equation (10):

$$f_{it} = \frac{\sum_j |N_i| |r_j == 0|}{|N_i|} \quad (10)$$

Where $|N_i|$ denotes the number of times exercise i has been practiced from the first correct answer to the t moment, $r_j == 0$ denotes the wrong answer, and f_{it} is set to 0.5 if $|N_i|$ is zero.

The time interval from the last answer g_t and the student's own forgetting degree f_t can be spliced to obtain the forgetting behavior feature vector x_t^f :

$$x_t^f = g_t \oplus f_t \quad (11)$$

2.3.2 Knowledge tracking status

The inputs of this section are the combined features after fusing the student interaction information with the behavioral features, and the student interaction information vector is first computed:

$$e_t = \text{Onehot}(C(q_t, r_t)) \quad (12)$$

Where e_t denotes the student interaction vector, which can be obtained by uniquely hot coding the cross-features of the answer results with the exercise numbers, and the vector has a dimension of $2N$, which is twice the number of the practice questions, and the position corresponding to the exercise number in the first N bits of the vector is set to 1 if the answer is correct, and the position corresponding to the exercise number in the last N bits of the vector is set to 1 if the answer is incorrect, and the rest of the positions are set to 0.

Splice e_t with the learning behavior feature vector x_t^s and the forgetting behavior feature vector x_t^f to obtain the combined feature v_t :

$$v_t = e_t \oplus x_t^s \oplus x_t^f \quad (13)$$

Where, v_t contains behavioral feature information, but the dimension is high, which is not conducive to model training, so in this section, an auto-encoder is used to perform dimensionality reduction operations on the input information.

A self-encoder is a kind of unsupervised learning artificial neural network that can learn the hidden features in the input data and can reconstruct the input data with the new features learned. The self-encoder contains two parts: encoder and decoder. Among them, the encoder extracts features from the input information and obtains its higher-order representation, and the decoder reconstructs the higher-order representation of the input information into the input data. This process can be expressed as the following Equation:

$$u = \text{Encoder}(x) \quad (14)$$

$$y = \text{Decoder}(u) \quad (15)$$

The goal of the auto-encoder is to make the error between input x and output y as small as possible, so the information of the intermediate state u should be as complete as possible, so as to better reconstruct the output y . At the same time, the dimension of the hidden layer of the auto-encoder is set to be smaller than that of the output layer, so as to realize the dimensionality reduction of the input vectors, and ensure that as much as possible, the important information will not be lost. After the training of the self-encoder is completed, only the encoder needs to be retained and the combined features v_t are fed into the encoder to obtain the dimensionality reduced input vector v_t' :

$$v_t' = \text{Encoder}(v_t) \quad (16)$$

Next, the input vector v_t' with the corrected knowledge state h_{t-1}' is entered into the GRU unit to obtain the student knowledge state h_t at the current moment:

$$h_t = GRU(v_t', h_{t-1}') \quad (17)$$

Finally, according to the students' knowledge state h_t to predict the students' correct answer rate y_t , y_t is the predicted value of the students' correct answer rate in the next moment. After analysis, the factors affecting y_t are not only the students' knowledge level h_t at the current moment, but also the characteristics of students' forgetting behaviors from the t th answer to the $t+1$ th answer x_{t+1}^f . Therefore, the calculation process of y_t is shown in Equation (18):

$$y_t = \sigma(W_{out}(h_t \oplus x_{t+1}^f) + b_{out}) \quad (18)$$

Where W_{out} and b_{out} are the neural network parameters for the prediction part, σ denotes the activation function *Sigmoid*, and $h_t \oplus x_{t+1}^f$ denotes the splicing of the student's knowledge state h_t with the forgotten behavioral features x_{t+1}^f . After the transformation of activation function *Sigmoid*, the answer correctness vector y_t, N with dimension N is obtained to represent the number of exercises, y_t and the i th dimension corresponds to the correctness of the student's answer on the i th exercise.

3 Analysis of the effect of intelligent party-building education in colleges and universities

3.1 Impact of wisdom education on students' performance in Civics and Politics

3.1.1 Experimental grouping

After the completion of the theoretical class teaching, the learning effect of the learners will be different due to individual differences, in order to minimize the impact of the individual's a priori knowledge on the experimental results, it is necessary to remove the extremes of the experimental data before the wisdom of the practical teaching is carried out, so after the completion of the theoretical learning, a pre-test of a duration of 20 minutes will be arranged, containing 20 multiple-choice questions, with a total score of 100, and the number of students meeting the experimental requirements is 115, based on the scores of the test will be more than or lower than two standard deviations of the students are removed, to determine the number of people who meet the requirements of the experiment is 115, and finally the experimental subjects will be randomly and evenly assigned to the experimental group of 2 different conditions, of which 56 people in the group of using the smart party education and 59 people in the group of not using the smart party education at the same time, selecting the 32 Civics teachers of the T colleges and universities as a sample of the classroom Civics competence of the teachers in this study.

3.1.2 Descriptive statistical analysis of dependent variables

In this study, the experimental data were analyzed using SPSS 24.0 software for descriptive statistics with teaching style and smart teaching environment as independent variables and cognitive load,

value identity, knowledge acquisition, knowledge transfer, and knowledge retention as dependent variables. Table 1 shows the descriptive statistics of the dependent variables, reporting the specific values of each dependent variable with or without the use of teaching methods in the smart party environment, where the values under the columns of the two experimental groups represent the mean values and SD represents the standard deviation. In the descriptive statistics of the three dependent variables of knowledge acquisition, knowledge transfer, and knowledge retention, the experimental group outperformed the control group, and the difference in the means of the data for the three dependent variables was 7.5026, 8.878 and 9.02, respectively.

Table 1. Descriptive statistics of dependent variables

Dependent variable	Ideological and political education			
	Intelligent party building education			
	Control group	SD	Experimental group	SD
Cognitive load	3.4563	0.785	4.0156	0.245
Value identity	4.5696	0.578	5.0654	0.145
Cognitive mastery	75.6524	5.986	83.155	5.163
Knowledge transfer	65.785	4.978	74.663	5.452
Knowledge retention	51.533	4.785	60.553	4.785

Cognitive load and value identity are scaled variables, and frequency histograms can be used to visualize the values of these two dependent variables.

3.1.3 Tests of reliability and validity of measurement instruments

The 5-point Likert scale was used to design the measures of cognitive load and value identity, and it was necessary to test the reliability of these two dimensions. In this study, Cronbach's coefficient and composite reliability (CR) were used to determine the reliability of the questionnaire data. Table 2 shows the constituent reliability and convergent validity. The Cronbach's values for all constructs ranged from 0.875 to 0.884, which all exceeded the recommended threshold of 0.7. All CR estimates also exceeded 0.7, which suggests that the questionnaire data have a high degree of consistency and reliability. This study evaluated convergent validity by examining the average variance extracted (AVE) and factor loadings for all indicators. Factor loadings were generated by a validated factor analysis (CFA). The AVE values were 0.765 and 0.841, which greatly exceeded the recommended threshold of 0.5, indicating that the questionnaire's items are a good measure of cognitive load and value identification.

Table 2. The composition of the letter and the validity of convergence

Dimension	Topic	Mean	SD	Loading	T-value
Cognitive load					
Cronbach's Alpha=0.884	CL1	4.5652	1.3454	0.8785	53.5663
CR=0.918	CL2	4.1985	1.4785	0.8966	45.6332
AVE=0.765	CL3	4.3795	1.3045	0.8452	23.4996
	CL4	4.0632	1.3785	0.8633	37.8745
	CL5	4.4785	1.2636	0.8452	32.4898
Value identity					
Cronbach's Alpha=0.875	VI1	5.4613	0.7894	0.8451	34.1633
CR=0.903	VI2	4.9874	0.8561	0.7645	21.3469
AVE=0.841	VI3	5.1643	0.8966	0.8963	43.6369
	VI4	5.1649	0.9451	0.8785	40.1278

	VI5	5.5643	0.7963	0.7633	23.4633
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3.1.4 Multi-factor analysis of variance (ANOVA)

Multifactor ANOVA is a common statistical method used to study the effects of multiple independent variables on a dependent variable. Simultaneously examining the effects of multiple independent variables on the dependent variable and testing for an interaction effect between them is possible. Interaction effect means that the effect of multiple independent variables on the dependent variable is not a simple additive relationship but an interactive relationship. The significance of the main effect is affected by interaction effects in multifactor ANOVA, so it is necessary to test and analyze interaction effects.

Table 3 shows the results of two-factor ANOVA for each variable, in which DF stands for degrees of freedom, SD stands for standard deviation, F is the effect value, and P stands for significance. This experiment utilizes multi-factor ANOVA to analyze the effect of different levels of independent variables on the dependent variable. Specifically, the construction of intelligent party-building education and teaching strategies (using/not using the principle of pre-training and generative learning strategies) are taken as the independent variables in this multi-factor ANOVA, and the cognitive load, value identity, knowledge mastery, knowledge transfer, and knowledge retention are taken as the dependent variables, and the within-group variance contrasts, and between-group ANOVA contrasts were utilized to test whether there were significant individual and interaction effects of the independent variables on the dependent variables, and the following conclusions were drawn:

- 1) The mean effect size of the independent variable smart party building environment on cognitive load under different teaching styles is 0.043, and the effect is significant with a p-value of 0.014. Further cross-effects analyses were done to find out that there is an interaction effect of teaching strategies and smart Party building education on cognitive load $F=2.633$, $p=0.037$.
- 2) By doing the main effect analysis on the effect of the dependent variable, it was found that the mean effect size of the effect of teaching methods on value identity in the smart party building environment was 1.4633, with a significant effect ($P=0.019$).
- 3) The effect of smart party building on knowledge acquisition in different teaching methods is not significant. At this time, $P = 0.2641$. After the analysis of cross-effects, there is an interaction effect between the effect of teaching strategy and smart party building on knowledge acquisition. The effect value and significance are 4.7933 and 0.0534, respectively.
- 4) The effect of the effect of smart party building on knowledge transfer under different teaching methods is not significant, and the effect of the effect of teaching methods on knowledge transfer under smart party building is also not significant, and the cross-effects analysis found that there is no interaction effect between the effect of teaching strategies and smart party building on knowledge transfer, with a p-value of 0.0674, which is greater than 0.05.
- 5) The mean effect size of the independent variable wisdom party building on knowledge retention under different teaching styles is 0.8794, and the significance is 0.6941. The effect is not significant. The mean effect size of the effect of teaching styles on knowledge retention under smart party building is 0.7169. At this time, the p-value is 0.4963. However, after further cross-effects analysis, the two interactions have a significant effect on knowledge retention. At this time, $F=5.6941$, $p=0.046$.

Table 3. The results of the variance analysis of two factors

Knowledge load				
Variable	Df	SD	F	P
Intelligent party building environment	1	1.786	0.043	0.014
Teaching mode	1	1.345	0.017	0.534
Intelligent party building * teaching mode	1	1.693	2.633	0.037
Value identity				
Variable	Df	SD	F	P
Intelligent party building environment	1	0.8633	0.3669	0.263
Teaching mode	1	1.1363	1.4633	0.019
Intelligent party building * teaching mode	1	0.6796	1.6987	0.046
Cognitive mastery				
Variable	Df	SD	F	P
Intelligent party building environment	1	6.4633	0.1578	0.2641
Teaching mode	1	8.9634	2.6394	0.0163
Intelligent party building * teaching mode	1	5.6364	4.7933	0.0534
Knowledge transfer				
Variable	Df	SD	F	P
Intelligent party building environment	1	4.7963	0.2639	0.6984
Teaching mode	1	6.7963	0.5964	0.1596
Intelligent party building * teaching mode	1	6.0364	3.6984	0.0674
Knowledge retention				
Variable	Df	SD	F	P
Intelligent party building environment	1	9.7946	0.8794	0.6941
Teaching mode	1	8.9633	0.7169	0.4963
Intelligent party building * teaching mode	1	6.4691	5.6941	0.046

3.2 Survey Results and Analysis of Teachers' Classroom Civics Competence

3.2.1 Distribution of Teachers' Classroom Civics Quality Levels

Figure 4 shows the status of the teachers' ability to course ideology and politics. The 32 ideology teachers in college T have a better overall understanding and recognition of the concept of course ideology and politics and a better knowledge reserve of ideology and politics, in which the mean values of the awareness dimension, the ability dimension, and the implementation dimension are 12.8658, 13.3511, and 23.7399, respectively. It can be seen that the ideology teachers in college T have a better ability to implement the wisdom of the Party's education. As for the standard deviation, the range of standard deviation of the three dimensions is between [2,5], which is within the acceptable range, and the results of this survey on teachers' classroom Civics competence are highly credible.

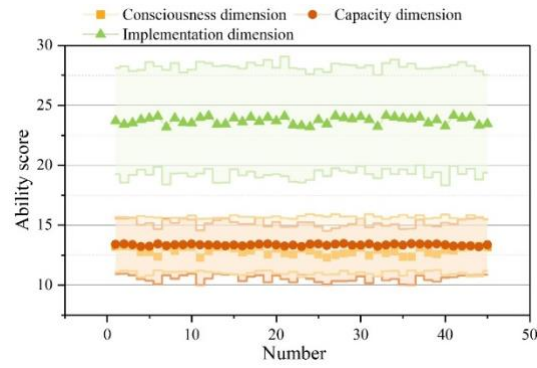
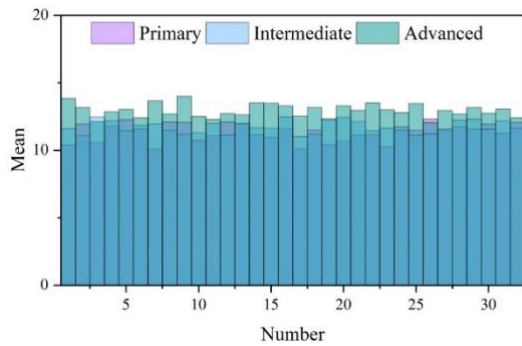


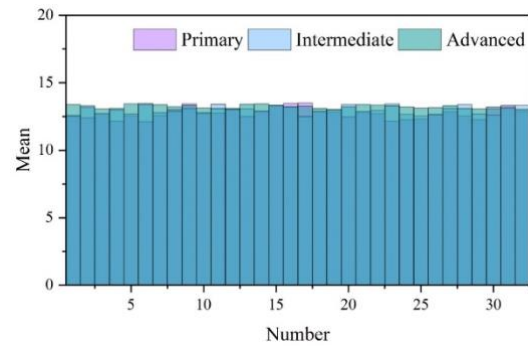
Figure 4. The political ability of the teacher's course

3.2.2 Distribution of different teachers' classroom Civics competence

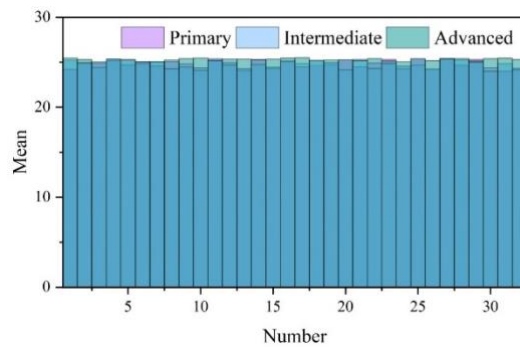
The results of the comparison between different titles showed that there were significant differences in the awareness of Curriculum Civics among junior, intermediate, and senior teachers. Figure 5 shows the status of teachers' competence in the civics curriculum in different titles, with Figure (a) showing the awareness dimension, Figure (b) showing the competence dimension, and Figure (c) showing the implementation dimension. Further analysis reveals that senior title teachers' awareness of course ideology is significantly higher than that of junior title and intermediate title teachers, and all three dimensions of senior title teachers' ideology awareness are higher than that of junior and intermediate title teachers. The gap between the civic and political awareness of junior and intermediate-title teachers is not big. The difference is 0.3647, 0.2366, and 0.0203, respectively, which are all within 1.



(a) Consciousness dimension



(b) The ability dimension



(c) Implementation dimension

Figure 5. The ideological and political ability of different titles

4 Practical Path of High-quality Development of Party Building Education in Colleges and Universities

4.1 The leading role of ideological education

Ideological and political education is the core and soul of party-building education in party schools, the cornerstone of cultivating the political quality of party members and cadres, and an important guarantee for promoting the comprehensive development of party members and cadres. At the same time, party schools should also encourage party members and cadres to develop their personalities and give full play to their strengths, and through diversified teaching and activities, guide them to establish a correct outlook on life, improve their personality, and constantly improve their personal qualities.

4.2 Combining Modern Technology to improve the relevance of party building work

The requirements of party building in the new era need to be combined with the design of content that meets practical needs. Teaching methods such as case analysis and problem orientation can be used to highlight highly targeted themes and practices and to guide students toward deep thinking and learning. As an important platform for the learning, training, and education of Party members and cadres, Party schools should closely integrate the actual situation and constantly improve and innovate their working methods to better meet the learning needs of Party members and cadres.

4.3 Use of aids to improve the effectiveness of teacher education

An excellent teaching team is necessary for the high-quality development of party-building education in party schools in the new era. The educational impact of the party school is directly related to the learning quality of party members and cadres, as well as the effectiveness of party-building work. In order to provide high-quality party-building education in party schools, the first step should be to optimize the construction of the teaching team and continuously improve the level of education and teaching.

4.4 Strengthening Party-building informationization and adapting to the needs of the times

One practical path for the high-quality development of party-building education in party schools in the new era is to strengthen party-building education through IT to meet the needs of the times. Party-building digitization refers to the use of modern information technology to carry out information, digitalization, network management, and operations in party construction and education. In the era of information technology, party-building work should also keep pace with the times, fully utilize the advantages of information technology, and improve the quality and efficiency of party-building work.

5 Conclusion

This paper constructs a theoretical model of intelligent party-building education in colleges and universities and proposes a model of predicting students' Civic and Political performance and knowledge tracking oriented to intelligent party building according to the Reform of party-building curriculum in the intelligent party-building education model. Controlled experiments were conducted to analyze the impact of smart education on students' Civics and Political Science learning and teachers' classroom Civics and Political Science ability after designing the experimental grouping. Among the five elements of students' Civics achievement measures, the experimental group scored

better than the control group in the three dependent variables of knowledge acquisition, knowledge transfer, and knowledge retention, with difference values of 7.5026, 8.878, and 9.02, respectively. In the reliability analysis of the survey, the Cronbach's alpha values of Cognitive Load and Value Identity were 0.884 and 0.875, which were greater than 0.7, respectively, and the AVE values were 0.765 and 0.841 respectively, which are much more than the threshold value of 0.5, this survey can measure the cognitive load and value identity well. In the Distribution of the Civics competence of teachers with different titles, the three dimensions of Civics competence of teachers with senior titles are higher than those of junior and intermediate, while the gap between teachers with junior and intermediate titles is not big, within 1. The intelligent party-building education has produced good results, as can be seen. According to the analysis results, this paper proposes the optimization path of party-building education in colleges and universities from the four aspects of ideological leadership, the relevance of party-building work, the flexible use of auxiliary tools, and the strengthening of party-building information construction.

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