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Intelligent Transformation Path of the Teaching Mode of Civics and Political Science Courses in Colleges and Universities under the Digital Education Environment in the New Era

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SUMMARY: *The Intelligent Civics can be defined as a hypothetical path towards the modernization of ideological and political education in the age of artificial intelligence. Thus, the intelligent transformation of Civics teaching in higher education institutions has become one of the key issues in the realm of educational discussion. This study claims that in the digital age when students learn using the digital education environment, traditional methods of deep knowledge tracing fail to reflect their behavioral traits. In order to compensate for the above deficiency, the improved deep knowledge tracing approach which incorporates corrections alongside behavioral features has been suggested, and referred to in English as the DKT-Correcting model. By incorporating it into the learning platform, the educators will be able to track in real time the degree to which students understand the material, help them fill any potential learning gaps, pace the lessons in accordance with their needs, and gradually develop a customized intelligent tutoring system for the intelligent upgrade of Civics instruction in colleges and universities of the digital era. The DKT-Correcting model was used in order to measure the level of mastery of knowledge points by students in the Civics and Political Science class. With regard to knowledge point M2, out of 100 participants, 20 students failed to master the topic (20%), while 65 showed partial mastery (65%), with only 15% mastering it fully. The results suggest that the introduced DKT-Correcting model positively affects the process of intelligent transformation of Civics and Political Science teaching in higher education institutions.*

KEYWORDS: *behavioral characteristics; DKT-Correcting model; teaching mode of Civics and Political Science class; intelligent transformation; personalized intelligent guidance system*

1 Introduction

In the context of enhancing reforms in Civics teaching in higher institutions of learning, the concept of opening the door to Civics has increasingly become an important criterion for gauging improvements in instructional efficiency. With the increasing application of artificial intelligence, big data, virtual simulation, and other technologies, higher education has been profoundly transformed, and new forms of developmental pathways such as core-literacy orientation, interdisciplinary practices, harmonization between teaching and evaluation, harmony between technology and learning, and deep learning have emerged [1-4]. In the current period of industrial revolution, intelligent technology has been integrated into fields

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such as economy, science, and technology, and has similarly revolutionized the practices of education [5]. Within this context, digital intelligence technology that aligns with the process of informatization and intelligentization of higher education is capable of improving the quality and effectiveness of Civics instruction, promoting the development of Civics teachers, and optimizing the curriculum system through innovation [6-9].

The intelligent approach towards the evolution of curriculum reforms becomes one of the significant trends and major concerns in Civic and Political Science education. At the same time, the development of intelligent techniques and creation of intelligent courses in Civics and Political Science are important ways for the promotion of ideological and political educational modernization. Under these conditions, using intelligent techniques in creating smart Civic and Political Science courses can be considered both an innovative way to ensure curricula reforms and a major goal to achieve in the course of curricula innovations in the contemporary world [10]. For developing a more intelligent and individualized education model, it is important to change teaching methods, ideas and classroom structures as well as form a more sophisticated and advanced teaching system regardless of some difficulties that exist regarding this issue [11-15]. Therefore, colleges and universities should begin by exploring the smart transformation of Civics and Political Science courses and seek diversified pathways for intelligent reform.

The study uses big data, computer science, and information technologies as technological bases to build a deep knowledge tracing model for teaching Civics. However, traditional models tend to ignore the behaviors of students. In order to make up for this deficiency, this paper designs an improved deep knowledge tracing model, which considers both behavior and correction aspects together. Thus, the DKT-Correcting model designed in this paper is based on gated recurrent unit (GRU) neural network. The research then explores the intelligent transformation of Civics and Politics courses based on digital-education environment, building a personal intelligent tutoring system for teaching Civics and Politics courses. The credibility of the research findings is also verified through experimental analysis of the model and tutoring system tests.

2 Exploration of Intelligent Transformation Path of Civics Class Teaching Mode in Colleges and Universities

In the modern age of intelligent information technology, traditional theories of education are gradually influenced by scientific and technological developments, changes in ways of thinking, and even overall social change. The application of artificial intelligence and big data technologies has already had significant effects on the teaching of Civics and Political Science in universities. In the digital era, where education is concerned, the creation of a path toward intelligent innovation in Civics education is aided by big data, computer science, and information technology. These will contribute to making the content of the study more interesting and relevant to students through the use of knowledge tracing techniques that can accurately determine the current status of the learner and his/her problems in learning, provide appropriate teaching materials, and thus further innovating in education.

2.1 Deep knowledge tracking model

Within the modern-day digital education framework, models that can predict the performance of students can help teachers gauge the overall proficiency of learners. Nonetheless, considering the fast growth in online learning environments and the detailed classification of knowledge points, the use of only knowledge-level prediction models might be insufficient to offer personalized suggestions. Knowledge tracing stands out as a vital area of study within the field of Civics instruction at institutions of higher learning, considering that it provides information on the proficiency of students in various knowledge points, tracks changes in their learning status during the process, and predicts their future performance. Despite the outstanding predictive performance of existing deep knowledge tracing models, most of these models disregard the behavior of students. Hence, to overcome this challenge, a new deep knowledge tracing model that employs correction techniques and student behaviors is introduced, and this model is called DKT-Correcting. The proposed model is constructed using the recurrent gated unit neural network (GRU). Where the input q_t is the student answer number, r_t is the student answer result, e_t denotes the student interaction information vector, x_t^s and x_t^f represent the student's learning behavioral characteristics and forgetting behavioral characteristics, respectively, and the output is the student's correct answer rate of prediction y_t and knowledge level state h_t .

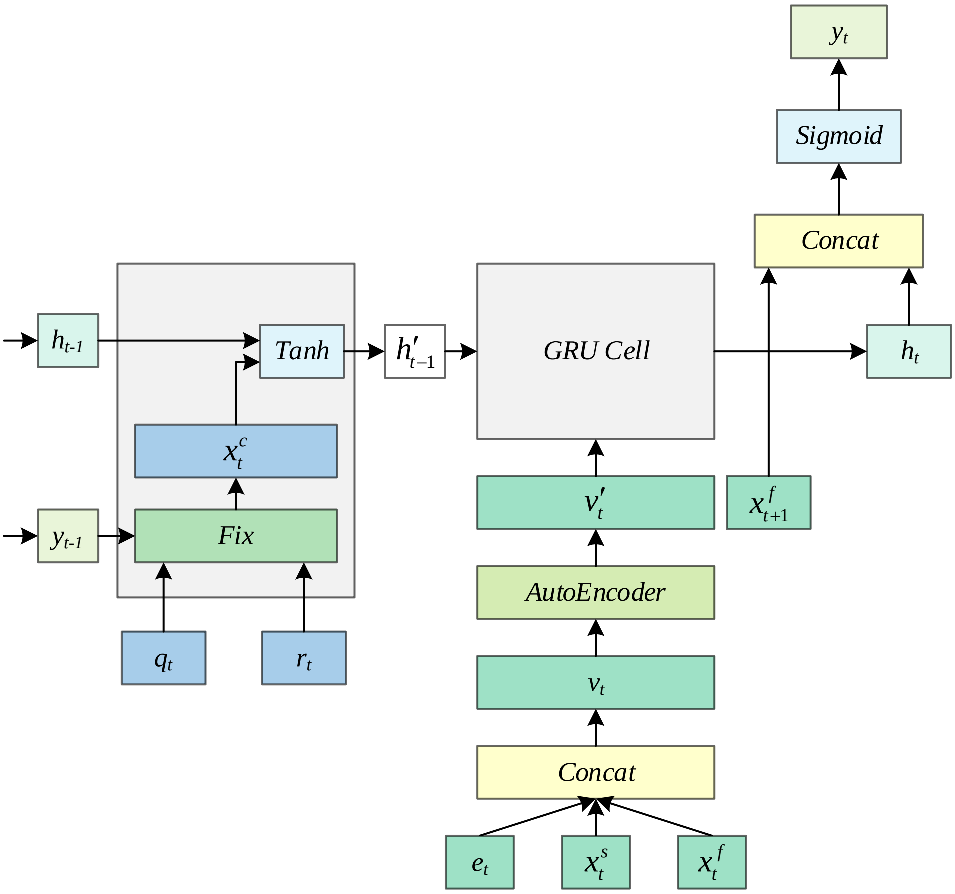

Figure 1: Overall structure of the model

2.1.1 Behavioral Characterization Constructs

The learning behavioral traits are associated with the collection of behaviors from the students as they answer the questions posed to them, which include their reaction times and help-seeking frequencies. However, in most real-life scenarios, the datasets may not include a full record of the behaviors. Therefore, this research proposes two learning attributes, namely c_t and s_t, computed using computational statistics. c_t stands for the number of times a student successfully responds to the same problem. Meanwhile, st is the indicator used to determine the student's learning efficiency.

$$c_t = \begin{cases} 0 & \text{Correct answers before the tth attempt} = 0 \\ 1 & 1 \le \text{Correct answers before the tth attempt} < 5 \\ 2 & \text{Correct answers before the tth attempt} \ge 5 \end{cases} \tag{1}$$

The s_t statistic is calculated by calculating the number of previous successful attempts at the same problem before the present attempt. Since this attribute may have a great degree of variance in datasets, it is classified based on specific criteria to ensure the experiment's effectiveness is not undermined. The success rate of the problems is dependent on the number of trials made and the variability of the responses made. Thus, it can be expressed as the proportion between the number of correct responses and the total number of trials. Whenever a student comes across a new problem, the success rate is assumed to be equal to 0.5. With this assumption, the learning efficiency of the learner can be categorized as follows.

$$s_t = \begin{cases} 0 & 0 \le \text{Accuracy rate before the tth attempt} < 0.33 \\ 1 & 0.33 \le \text{Accuracy rate before the tth attempt} < 0.67 \\ 2 & 0.67 \le \text{Accuracy rate before the tth attempt} \le 1 \end{cases} \tag{2}$$

Since these learning features are associated with the practice items at time t , a cross-feature approach is adopted to fuse the learning features with the exercise identifiers, and one-hot encoding is then applied. The resulting learning-feature coding is illustrated in Figure 2.

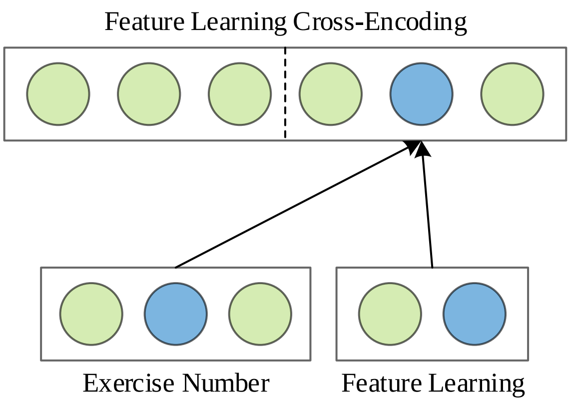

Figure 2: Learning feature coding

The crossover feature is calculated as shown in equation (3):

$$C(q_t, s_t) = q_t + \max(q+1) * s_t \tag{3}$$

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-hot 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 obtain the learning behavior feature vector x_t^s. That is:

$$x_t^s = Onehot\left(C\left(q_t, s_t\right)\right) \oplus Onehot\left(C\left(q_t, c_t\right)\right) \tag{4}$$

Time interval since last answer $g_t = \left(g_{1t}, g_{2t}, \cdots, g_{it}, \cdots\right)$, g_t dimension is equal to the number of exercise questions, and g_{it} denotes that the t th answer is a time interval since the last answer to the i th time interval from the last answer to the i exercise question. The student's own forgetting level f_t is constructed from the answer records, $f_t = \left(f_{1t}, f_{2t}, \cdots, f_{it}, \cdots\right)$, and f_{it} denotes the error rate of the student's answers on the i th exercise question until the t th answer, calculated as in equation (Eq. error rate, calculated as shown in equation (5):

$$f_{it} = \frac{\sum_j^{|N_i|} \left| r_j == 0 \right|}{\left| N_i \right|} \tag{5}$$

where $\left|N_i\right|$ denotes the number of times exercise i has been practiced from the first correct answer to the t moment, $r_j == 0$ denotes an incorrect answer, and if $\left|N_i\right|$ is 0 then f_{it} is set to 0.5. A vector of forgetting behavioral features x_t^f can be obtained by splicing the time interval g_t from the last answer with the student's own degree of forgetting f_t. To wit:

$$x_t^f = g_t \oplus f_t \tag{6}$$

2.1.2 Knowledge level correction

At every moment, the deep knowledge tracing framework receives the observed response of the learner as an input signal, and this signal is aligned with the estimated output generated in the preceding moment. Accordingly, this part develops a knowledge-level adjustment unit to judge whether the earlier prediction is accurate by matching the previous estimated result with the information observed at the current moment, and then revises the previously produced knowledge representation when necessary.

More specifically, the role of this adjustment unit is to update the knowledge state generated in the earlier moment on the basis of both the former output and the newly arrived input at the current moment. To begin with, the model must determine whether the earlier estimation is correct, and the corresponding computation is given below:

$$p_t^c = y_{t-1} \odot Onehot\left(q_t\right) \tag{7}$$

$$p_t^w = \left(1 - y_{t-1}\right) \odot Onehot\left(q_t\right) \tag{8}$$

where $\odot$ denotes the multiplication of the corresponding positional elements of the vector to obtain a vector of the same length, y_{t-1} is the prediction result of the previous time step, which denotes the probability of answering each question correctly, and $\left(1 - y_{t-1}\right)$ denotes the probability of answering each question incorrectly. The answer number q_t is uniquely hot coded and the $\odot$ operation is performed with the output y_{t-1} of the previous time step to be able to obtain the answer-correct vector p_t^c, the dimension of p_t^c is equal to the number of questions, and the value at the position corresponding to the question number q_t is equal to the probability of answering the question correctly, and the rest of the positions are zero. Similarly, the $(1-y_{t-1})$ operation with $\odot$ can obtain the answer error vector p_t^w. According to the real answer result, the correct answer vector p_t^c is spliced with the answer error vector p_t^w to get the correction vector x_t^c containing the correctness of the answer result, and the formula is shown below:

$$x_t^c = \begin{cases} p_t^w \oplus p_t^c & r_t = 0 \\ p_t^c \oplus p_t^w & r_t = 1 \end{cases} \tag{9}$$

where $\oplus$ denotes the vector splicing operation, r_t denotes the answer result, 0 means wrong answer, 1 means right answer.

After obtaining the correction vector x_t^c, it is inputted into the correction module together with the knowledge state h_{t-1} outputted by the GRU unit in the previous time step, and the corrected knowledge state h'_{t-1} is obtained, which is calculated inside the correction module as shown in Equation (10):

$$h'_{t-1} = \sigma\left(W_1 h_{t-1} + W_2 x_t^c\right) \tag{10}$$

where σ denotes the activation function $\tanh$ and W_1 and W_2 denote the parameter matrices.

2.1.3 Knowledge status tracking

This part takes as input the fused representation obtained by combining learner interaction information with behavioral features, and the learner interaction vector is first defined as follows:

$$e_t = Onehot\left(C\left(q_t, r_t\right)\right) \tag{11}$$

Here, e_t represents the learner interaction vector, which is constructed by uniquely encoding the cross-feature formed by the response outcome and the exercise index. Its dimension is $2N$, namely twice the number of practice items. When the response is correct, the position associated with the exercise index in the first N entries is assigned 1; when the response is incorrect, the corresponding position in the latter N entries is assigned 1, while all remaining entries stay 0. The integrated feature v_t is then formed by concatenating e_t, the learning-behavior vector x_t^s, and the forgetting-feature vector x_t^f:

$$v_t = e_t \oplus x_t^s \oplus x_t^f \tag{12}$$

Although v_t, preserves behavioral-feature information, its dimensionality is relatively high and thus unfavorable for model training. For this reason, a self-encoder is introduced here to reduce the dimension of the input representation. As illustrated in Fig. 3, the self-encoder consists of an encoder and a decoder. In this structure, the encoder extracts higher-level representations from the original input, whereas the decoder reconstructs the input data from these higher-level representations. The whole procedure can be written as the following equation:

$$u = Encoder(x) \tag{13}$$

$$y = Decoder(u) \tag{14}$$

The purpose of the autoencoder is to minimize the discrepancy between the input x and the reconstructed output y, so that the intermediate representation u can preserve as much information as possible and enable more accurate reconstruction of y. Meanwhile, the hidden layer of the autoencoder is designed to be smaller than the output layer, allowing the dimension of the input representation to be compressed while retaining the most important information to the greatest extent possible. After training the self-encoder is completed, only the encoder is kept, and the fused feature v_t is passed through the encoder to obtain the reduced-dimensional representation v_t', namely:

$$v_t' = Encoder(v_t) \tag{15}$$

Then, the input vector v_t' with the corrected knowledge state h_{t-1}' is input into the GRU unit to obtain the student's knowledge state h_t at the current moment, the basic structure of the GRU and the calculation process:

$$h_t = GRU(v_t', h_{t-1}') \tag{16}$$

Finally, the students' answer correctness y_t is predicted based on the students' knowledge state h_t, and y_t is the predicted value of the students' answer correctness at the next moment. After analysis, the factors affecting y_t are not only the student's knowledge level h_t at the current moment, but also the characteristics of the forgetting behavior x_{t+1}^f from the student's t th answer to the $t+1$ th answer. Therefore, the calculation process of y_t is shown in equation (17):

$$y_t = \sigma\left(W_{out}\left(h_t \oplus x_{t+1}^f\right) + b_{out}\right) \tag{17}$$

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 students' knowledge state h_t with the forgetting behavioral features x_{t+1}^f. After the activation function $Sigmoid$ transformation, the answer correctness vector y_t with dimension N is obtained, N denotes the number of exercises, and the i th dimension of y_t corresponds to the student's answer correctness on the i th exercise.

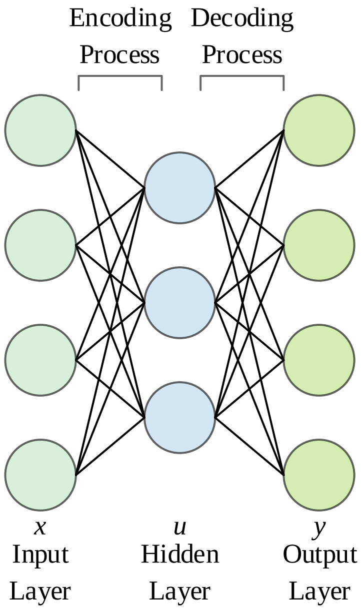

Figure 3: Autoencoder structure

2.2 Personalized Intelligent Guided Learning System Design

Considering the fast pace of development within digital learning environment settings and the shift towards intelligent instruction, online personalized smart guidance learning systems have become a significant learning tool for students in modern times. Specifically, it should be stressed that in the context of the post-pandemic period, many universities have discovered the shortcomings of face-to-face Civics instruction. In this subtopic, the knowledge tracing model used by the web-based learning system allows tracking the students' understanding of Civics topics and detecting any possible deviations in their learning process, which would make it possible to adjust the instruction strategies accordingly. Moreover, it helps evaluate the instruction methods used by the Civics teachers and analyze them in order to improve instructional strategies and planning schedules. By applying the knowledge tracing model, the intelligent improvement of Civics instruction at universities can be achieved by designing a personalized smart teaching support system.

2.2.1 System requirements analysis

The overall functional requirements structure of the personalized wisdom guidance system is shown in Figure 4. The personalized wisdom guidance system has two core functional requirements, one of which is to display the student user's Civics course information and provide a personalized student portrait display interface to display the learner's own Civics learning progress data, Civics learning ability parameters and other data. The second is to recommend personalized Civics exercises for students according to their Civics learning ability level. In addition, the system manages the privileges of the logged-in users, who are divided into student users and teacher users. Teacher users can add, delete, change and check student user information, course information and question bank data. To summarize, the functional requirements of the system are divided into three main blocks, which are user login, registration and permission management, student user function, and teacher user function. The following is a detailed description:

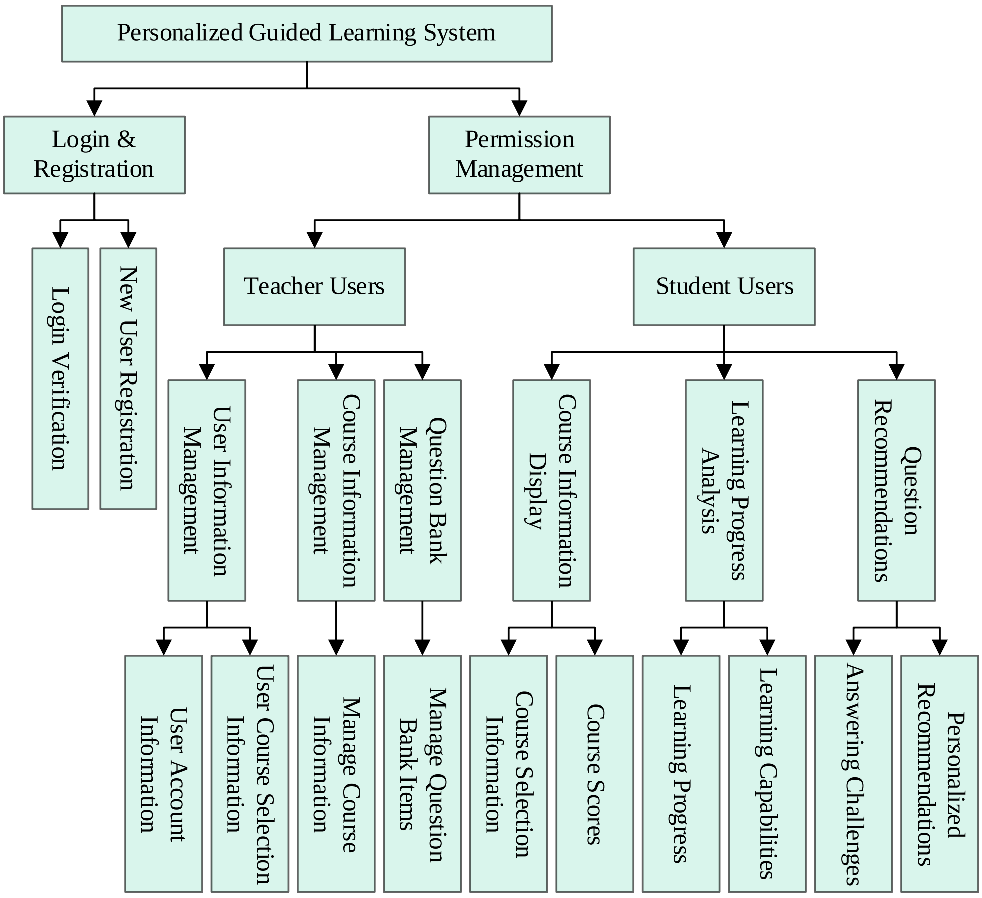

Figure 4: The overall functions of the personalized intelligent guidance system

(1) User Login Registration and Permission Management

This module mainly realizes the functions of new student/teacher user registration, login verification of registered student/teacher users and student/teacher user rights assignment. In the personalized smart tutorial system, users must be registered, unregistered users will be blocked by a pop-up window display, and registered users must pass the login verification operation when they re-login to the system. In addition, for the registered users in the system, when choosing the login identity, they must choose one of the student/teacher user identities. The system will automatically query the user_id of the current user in the database, and through the joint table query, it will match the corresponding user data for different users in the database and display them on the display page.

(2) Functions for Student Users

The system provides student users with the functions of displaying information of Civics courses, analyzing the learning situation of Civics and recommending Civics test questions. In the course information display interface, student users can view multiple types of information. For example, they can view the information of the selected course, such as the location of Civics courses, Civics teachers, etc., and the corresponding score information of the Civics courses; in the learning situation analysis interface, students can intuitively understand their own Civics learning progress and learning ability parameter information, and learn their Civics learning situation in the whole class from the rich graphical visualization interface; last but not least, in the test question recommendation interface, the system sets up two recommendation methods for learners to choose. Lastly, in the test question recommendation interface, the system sets two recommendation methods for learners to choose.

(3) Teacher User Functions

The functions provided by the Personalized Intelligent Guided Learning System for teacher users include class student information management, Civics course information management and course exercises library management. In the teacher user interface, teachers can query the personal information of students in the class, the list of selected courses and the grade information of the selected courses. In addition, the Personalized Intelligent Tutoring The system grants teachers access to student-group profiling functions, enabling them to directly examine parameters related to learners' Civics and Political Science performance as well as the difficulty levels of exercises completed by the whole class. Moreover, instructors are able to create, remove, modify, review, and output Civics course materials together with exercise resources within the platform.

2.2.2 System architecture design

The customized intelligent guidance platform adopts a browser/server architecture, and its overall framework is presented in Figure 5. The platform structure can be organized into the following three tiers:

The first level is the browser, which is the client. The client assumes the function of user input and system response output, that is, it completes the interaction with the user. The user enters the client in the form of a browser, displays web pages and interactive operations through the template engine and the front-end control system, and carries out the process of transferring certain necessary data with the server.

The second layer is the server side. The system uses SpringBoot as the server management framework to handle multiple requests from the client, and after processing the relevant business logic, it accesses the database layer and interacts with the business data.

The third layer is the data layer. After receiving data requests from the server side, the system will pull the information stored in the database and send back data to respond to the request and fulfill the business needs.

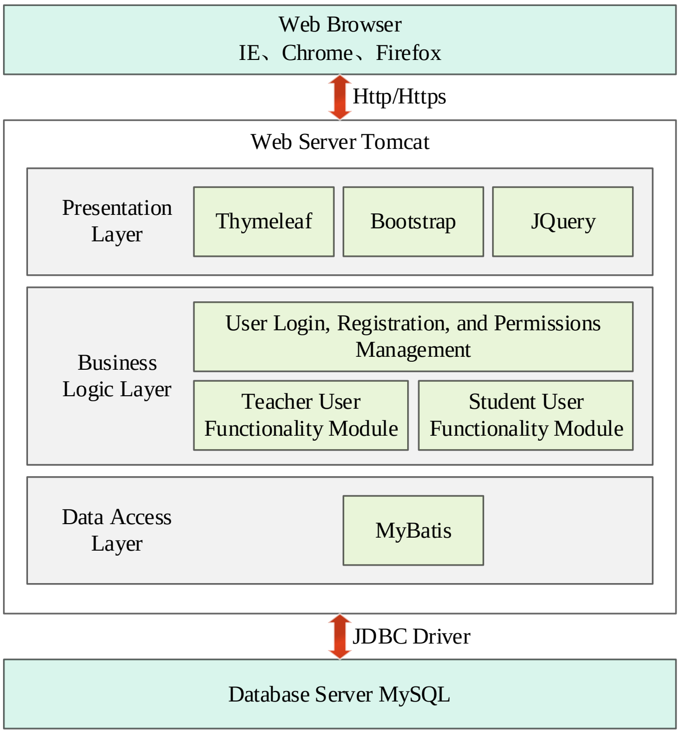

Figure 5: Overall system architecture design

2.2.3 Database design

In this subsection, the focus is on the design of the relational database, and the design process is strictly in accordance with the requirements of the personalized smart tutorial system. Strive to design a data table to ensure logical relevance, reduce redundant data while improving data utilization, in line with the three major database design paradigms. It also gives full consideration to the needs of different users for different business functions, runs the database under the Mybatis framework, and transmits the data to the front-end page to display the data, completing the system page display and system function realization.

3 Model and systematic empirical analysis

3.1 Model empirical analysis

This research includes the implementation of the knowledge trace into the university level Civics and Political Education (CPE). With the help of the DKT-Correction approach, the learning efficiency of university students undertaking such CPE course and its teaching method are examined. From a microscopic perspective, the knowledge competence of the learners is measured, thus making an evaluation on the importance of using the DKT-Correction model in improving the university CPE technique.

3.1.1 Experimental Objects

Implementation analysis was performed on university students for evaluating the application effect of teaching. The two classes of student participants were chosen as samples for the research, and the improved version was applied for diagnosing the knowledge level of the students concerning Civics. Finally, there were 100 valid quiz results recorded, including 48 in the first class and 52 in the second class.

3.1.2 Design of quiz questions

Upon consultation with the instructors handling ideological and political education courses and considering the curriculum development sequence and the research purposes, this research used the following testing materials: "Basic Principles of Marxism," "Theory and Practice of New Era Chinese Socialism," "Modern and Contemporary History of China Outline," and "Moral Basis and Legal Foundation." The authors designed the test items based on the standards of the revised curriculum standards, as shown in Table 1 below, which shows the correlation between each test item and its corresponding knowledge point. The tests were reviewed and finalized by teachers who teach these subjects at the forefront, yielding a test instrument with 25 objective-type questions, such as true or false, multiple-choice, and fill-in-the-blank. The students' answers to the test were dichotomized, with "0" representing a wrong answer and "1" representing a right answer.

Table 1: The correspondence between the question and the knowledge point

Question	M1	M2	M3	M4
1	0	0	1	0
2	0	1	0	0
3	1	0	0	0
4	0	0	1	0
5	0	1	0	0
6	0	1	0	0
7	0	0	1	0
8	0	0	0	1
9	0	0	0	1
10	1	0	0	0
11	1	0	0	0
12	0	0	1	0
13	0	0	0	1
14	1	0	0	0
15	1	0	1	1
16	1	0	0	1
17	1	0	0	0
18	1	0	0	0
19	1	1	1	0
20	0	1	0	0
21	0	1	0	0
22	0	0	0	1
23	0	0	0	1
24	0	0	0	1
25	0	0	1	0

3.1.3 Analysis of model applications

(1) Exercise Difficulty Analysis

The difficulty index for each item based on the raw response data can be calculated as the ratio of incorrect responses to the total number of responses submitted by all students taking the quiz. Items whose difficulty indices range between 0 and 0.408 can be considered easy, items with difficulty indices in the interval [0.408, 0.703) can be considered medium, and hard items have difficulty values within the range [0.703, 1]. The histogram showing the distribution of item difficulties in our dataset is illustrated in Fig. 6. Here, the abscissa refers to the item number, while the ordinate represents the difficulty coefficient. An orange line represents the boundary between easy and medium items, whereas the boundary between medium and hard items is represented by a magenta line. There are 2 hard items, 8 medium items, and 20 easy items in this dataset; easy items make up more than half of the total. Additionally, the average difficulty value of items included in the paper is found to be 0.373.

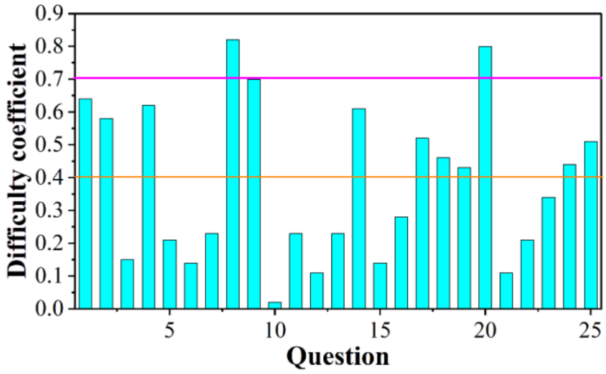

Figure 6: The difficulty distribution of the test questions

(2) Analysis of students' knowledge mastery

Through the use of the DKT-Correction framework to analyze the response records of the students, we can get the mastery level of every Civics knowledge point and then evaluate the learning efficiency of the course. In particular, by setting the 0.604 and 0.903 as the thresholds, the mastery level of Civics knowledge point will be classified into three strata. The probability less than 0.604 means that the Civics knowledge point is not mastered yet; the probability of [0.604, 0.903) means that the Civics knowledge point is partially well mastered; the probability greater than 0.903 means that the Civics knowledge point is totally mastered. According to the general analysis of Civics knowledge point, this section shows the results obtained through the DKT-Correction framework, hoping to assist the digital development of Civics education at higher educational institutes. From practice, the model can help students learn their own learning status, increase their awareness of their own level, and separate their mastered Civics knowledge point from unmastered ones. Therefore, the students need to pay attention to unmastered Civics knowledge points and consolidate learned ones.

Knowledge point M1 had a number of 100 students taking part in the test where 15 students were found to be at the level of not mastering this knowledge point, accounting for 15% of the total number, while the rest 85 students mastered the knowledge point, representing above 85% of the total number. A specific distribution of student mastery on this knowledge point is illustrated in Figure 7. As far as Civics knowledge point M1 is concerned, a comparatively good mastery level has been shown, but the percentage of students fully mastering the point was still lower than 90.3%, meaning that the highest mastery level was still unreachable.

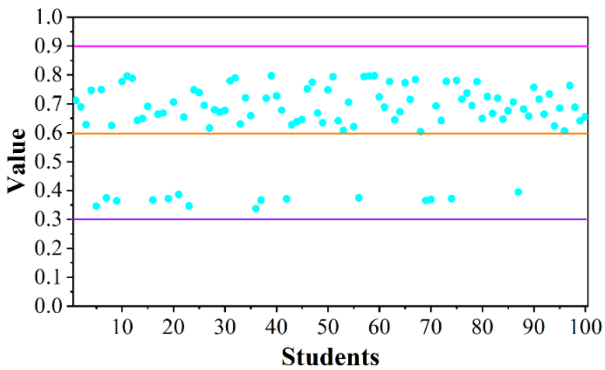

Figure 7: Knowledge Point 1: Students' mastery

On Civics knowledge point M2, out of 100 students who took part in the test, 20 students were not yet proficient in the knowledge point, accounting for 20% of the total number of students. Another 65 students showed greater proficiency, which translates to 65%, while 15 students attained maximum proficiency, equaling 15%. The graph below shows the proficiency levels of students in Civics knowledge point M2.

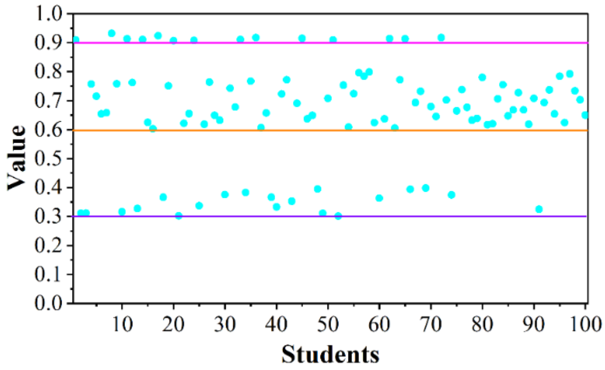

Figure 8: The students' mastery of knowledge point 2

In the case of Civics and Political Knowledge Point M3, out of 100 students who took part in the test, 25 did not attain mastery, and this constituted 25 percent of the total number. Twenty percent attained partial mastery, whereas 50 percent attained mastery in Civics knowledge point M3. The results show that there is significant disparity among students in terms of mastery of Civics knowledge point M3. There is notable polarization within the group of students under study.

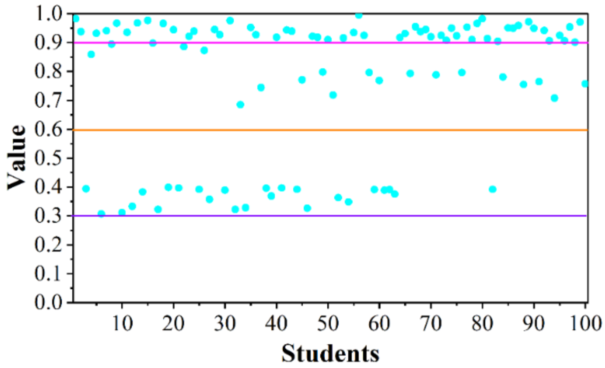

Figure 9: The students' mastery of knowledge Point 3

Civics and Political Knowledge Point M4: Among the 100 respondents who answered the test, only 27 respondents were not able to master the topic, accounting for 27%, while the remaining 73 respondents already reached a better mastery, which accounted for 73% of all respondents, while none of them reached full mastery, as shown in Figure 10. Just like knowledge point M1, the performance in Civics knowledge point M4 was also moderate, having a large number in the middle and no top performing students.

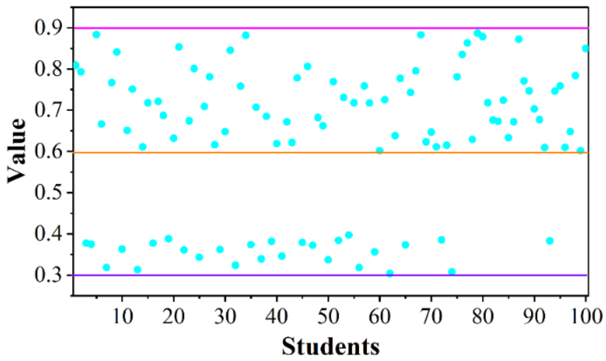

Figure 10: Students' mastery of knowledge Point 4

In general, the cohort performed relatively better in Civics knowledge point M1, whereas their proficiency in M2, M3, and M4 was relatively poor. In Civics knowledge point M1, over 85% of students were already familiar with the content, but only 15% had not mastered it. Nevertheless, there was still an insufficient number of high-achieving students. As a result, in future Civics classes, teachers ought to decrease their emphasis on overly simplistic content and focus more on the importance of the content so that they could continue improving themselves. Concerning Civics and Political knowledge points M2, M3, and M4, more than 28.9% of students failed to grasp the content well enough, and the polarization pattern became more pronounced. In such a case, teachers can leverage the knowledge-tracing method to guide students to review the relevant content, consolidate the important and difficult parts, and improve their practice quality. At the same time, more focus needs to be placed on students who struggle academically through counseling, while those performing well in their academics should also receive proper assistance.

3.2 Personalized Intelligent Guided Learning System Test

After empirical testing of the proposed framework, the practical importance of a deep knowledge tracing method, which incorporates an adaptive system as well as behavioral characteristics, has been revealed regarding the intelligent upgrade of Civics and Political Science courses in higher education institutions. In order to implement digital and intelligent transformation in the educational sphere related to this area, a tailored smart guidance system is designed using the framework of deep knowledge tracing. The platform will be tested from various angles through systematic evaluation to contribute to the intelligent development of instruction in this new era of digital learning.

3.2.1 Test environment deployment

This system test with vmware simulation to build a multi-machine multi-system test environment, the specific construction of the environment shown in Table 2.

(1) Install vmware virtual machine on this machine, use VMware to create three virtual operating system environments, respectively, Windows 7 64-bit, Windows 8 64-bit, Windows 10 64-bit, the system are Silverlight minimum requirements of 1TB memory, set up the network environment of the virtual machine, the test environment configuration is shown in Table 2. Because Windows XP is still used in the teaching system of some schools, the compatibility of this system with XP is also tested.

(2) Each type of browser is installed in the three operating systems, including IE7 or above versions and mainstream browsers with IE kernel as the core, such as 360, QQ Browser, Oceanic Browser, etc., Firefox 3.0 or above, Safari Browser, and Chrome Browser.

Table 2: Test environment configuration table

System version	Windows7 64-bit	Windows8 64-bit	Windows10 64-bit
Processor	4.6GHz	4.6GHz	4.6GHz
Hard disk	16G	16G	16G
Memory	1TB	1TB	1TB
Network adapter	NAT	NAT	NAT

3.2.2 Functional testing

In this paper, the functional evaluation focuses on user login and sign up, authorization control, student features, and teacher features. The results for this evaluation are shown in Table 3, where the number "1" represents a successful functional test while the number "0" represents an unsuccessful test in meeting the functional testing standards. Based on the performance results as well, it is clear that all of the functional components of the custom-designed smart guided learning system have met the standard with a score of "1". Therefore, the platform modules can support the intelligent reform approach for Civics and Political Science teaching in tertiary education.

Table 3: Functional test results

No.	System function test content	Test the expected results	Actual result	Remarks
001	User login and registration	1	1	Correct
002	Permission Management	1	1	Correct
003	Student user function	1	1	Correct
004	Teacher user function	1	1	Correct

3.2.3 Compatibility testing

The platform has been tested using both international and domestic rankings in regard to the browsers, and the results have been captured in table 4 below. For example, the Windows XP operating system can run IE9.0 but not IE10 and above, because IE10 and above have evolved into new generations that cannot operate on Windows XP; therefore, running the platform on Windows XP is not feasible. Furthermore, there are compatibility problems with Silverlight, which make it impossible for the platform to run on the Opera browser. The compatibility rate of the platform stands at 92.31%.

Table 4: Compatibility test results

Browser	Windows7 64-bit	Windows8 64-bit	Windows10 64-bit
IE11	√	×	√
IE10	√	√	√
IE9	√	√	√
IE8	√	√	√
IE7	√	×	√
Chrome	√	√	√
Firefox	√	√	√
Safari	√	√	√
Opera	√	×	√
360 Browser	√	√	√
QQ Browser	√	√	√
Sogou High-Speed Browser	√	√	√
2345	√	√	√

3.2.4 Response time testing

The results regarding homepage loading are shown in Figure 11. For the first loading of the homepage, the platform is expected to download the Silverlight application package, get the XML file, and parse it. This leads to comparatively more time expenditure. In cases of further access to the homepage, it will be necessary to retrieve and parse the XML file only. Thus, as shown in the figure, there is a slight difference between the first loading time and the reloading time, but both are below 3 seconds.

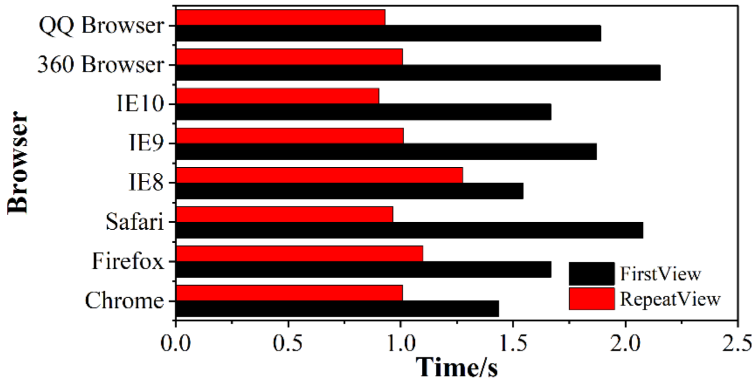

Figure 11: Test results of home page loading time

The response-time findings on login verification are shown in Figure 12. These findings mainly highlight the time frame starting from the moment when a user starts playing by pressing the play button that corresponds to the guidebook or an item in a list of resources and ending up with the process of login verification by the platform itself. Taking into account the performance findings depicted in the graph, it is clear that the login verification process takes less than 0.8 seconds.

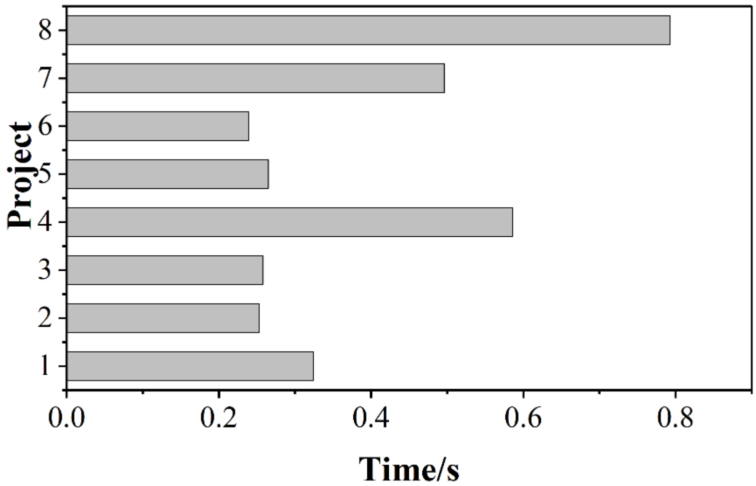

Figure 12: Login verification response time test results

Users switch resources through the catalog tree or keyboard shortcuts Left, Right, depending on the type of resources, the loading time will be slightly different, Figure 13 shows the loading time outcomes regarding the Civics course resources in the platform. As can be seen from the outcomes presented above, images have the quickest loading times, while videos have the slowest loading times. With regards to functionality, the platform is up to the mark, while as far as performance and cross-browser compatibility is concerned, the platform fulfills most expectations in this respect. Therefore, in conclusion, the customized intelligent guided learning platform has succeeded in meeting its objective through the knowledge tracing concept and has helped improve teaching methodologies in Civics and Political Science in higher education institutions.

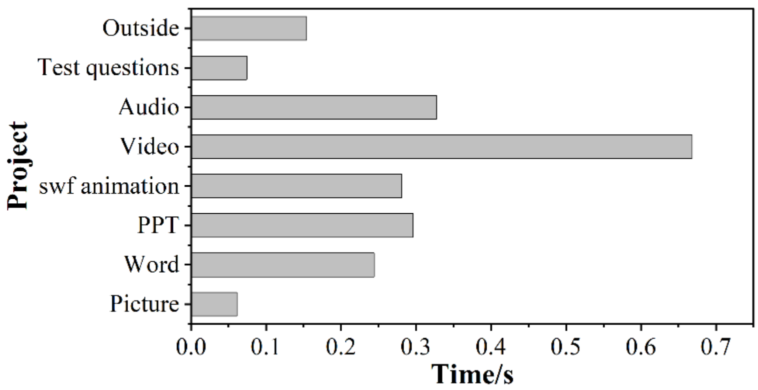

Figure 13: Comparison results of resource loading times

4 Conclusion

In order to realize intelligent and digital upgrading of Civics and Politics lessons in higher education, this paper establishes a smart guidance system based on a DKT framework and makes an empirical analysis of the smart guidance system from multiple angles.

(1) Based on the framework of DKT-correction, it is feasible to measure the mastery of all knowledge points for each learner during the Civics and Politics class. For example, based on knowledge point M1, out of 100 learners, 15 learners do not grasp the knowledge (15%) while 85 learners grasp it (85%). It shows that the framework of DKT-correction may better reflect the reality of learning process, clarify their level of knowledge mastery and distinguish what is mastered from what needs improvement. Therefore, learners could practice effectively, avoiding wasting time on useless things. In such a way, the study gives valuable help for intelligent upgrading in Civics and Politics lesson in higher education.

(2) After assessing the customized smart guidance system, it turns out that there is a strong compatibility and relatively short response time in the system, which is helpful for realizing intelligent transformation pathway in Civics and Politics course in higher education.

About the Author

Gang Shuai, was born in Miyi, Sichuan, P.R. China, in 1976. He received his doctoral degree from Beijing Normal University in China, and currently works at the School of Marxism Studies, Civil Aviation Flight University of China. His main research focuses on ideological and political education as well as youth issues studies.

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