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Exploration of the Path of Red Cultural Resourcesinto the Practice of Ideological andPolitical Education of College Students

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SUMMARY: *The successful implementation of the function that red cultural materials play in ideological education is hampered by a number of significant problems with their incorporation into ideological education in colleges and universities. In this paper, the virtual ideological learning environment is created using Unity3D, the three-dimensional model of the virtual intelligent body is imported, and the virtual intelligent environment perceptual field is obtained. First, the virtual ideological learning environment is modeled using 3DS MAX modeling tools, entity models, parent-child relationships of the components are adjusted, and materials are processed to obtain the three-dimensional object models, optimizing the models. By using FSM to construct the virtual intelligent body's decision-making cognition module, enhance the intelligent body's response time, and construct the physical models of the virtual ideological learning environment. Based on the knowledge features of red culture integration into civic and political education, learning routes are tailored and maximized.Detecting the effect of integrating red culture into Civics learning, the probability that the difficulty interval of A students' push questions falls in the range of 60 to 80 points is 53.3%, which is slightly higher than that of B and C students, because A students' achievements in Civics test are better than the other two, and there is a certain degree of personalization. The average score (93.24), the number of A grades (42), and the excellence rate (93.33%) of the experimental class are significantly higher than those of the control class when evaluating the students' civics learning ability. This suggests that the integration of red culture into college students' civics education has a positive experimental effect.*

KEYWORDS: *virtual civic learning environment; FSM model; learning path; knowledge characteristics; red cultural resources; civic education*

1 Introduction

College students' ideological and political education as a crucial course for carrying out the mission of developing moral integrity, is not only the teaching of knowledge, but also the key to the shaping of students' three outlooks, and carries the important task of cultivating students' core literacy [1]. In the course of revolution, building, and reform, the Party and the people created a strong faith, noble character, and tremendous spirit that are found in red resources, which is a high-quality educational material for the implementation of the task of cultivating morality [2]. Including it in political and ideological education is consistent with the state's basic needs for talent development. Traditional learning has certain limitations, students' motivation is not high, the learning effect is not good, and they can't really understand the content of ideological and political class and transform it into their own value

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literacy [3]. The dilemma faced by traditional teaching is that students have low motivation to learn, limited participation, and are difficult to truly understand and internalize the values in ideological and political classes, resulting in poor teaching effectiveness [4, 5]. With the deepening of educational reform, the educational philosophy emphasizing the cultivation of students' comprehensive literacy has gradually become mainstream. College students' ideological and political education must also be innovative in order to meet the demands of modern education. The utilization of red cultural resources offers a new direction in terms of ideological and political education reform, bringing a fresh perspective in breaking the monotony of conventional teachings by providing lively historical characters and narratives [6].

Ideological and political education carries the strategic mission of nurturing people and talents as the core path of casting souls and nurturing people in higher education in the new era. It is also the fundamental guarantee that colleges and universities will follow the path of socialist education and produce socialist builders and successors [7, 8]. Through systematic theoretical armament and practical infiltration, it integrates the Party's innovative theories into the whole process of talent cultivation, not only builds the foundation of ideals and beliefs for young students, but also refines their political character to take up the important task of rejuvenation, and promotes the fundamental task of establishing morality and cultivating people to take root in the in-depth fusion of knowledge transmission and value guidance, so as to cultivate the talents who can take on the important tasks by linking the realization of their personal values with the future destinies of the Party and the country. There is a clear ideological and political component to the red cultural resources [9]. As a unique resource for ideological and political education, the use of red cultural resources for ideological and political education necessitates that colleges and universities fully comprehend and apply the laws of ideological and political education, ideological and political education using red culture throughout the entire talent training process, boosting university students' cultural confidence, strengthening their patriotism, and raising the standard of talent training in colleges and universities. [10-13]. Under these circumstances, the integration of red cultural resources into ideological and political education in colleges and universities is a critical issue.

In this paper, based on the geometric modeling route, solid modeling is carried out for some complex 3D models, and the parent-child relationship is adjusted for them, and the material processing is also needed for them. Unity3D technologies will be used to construct the FSM architecture, and FSM may be used to describe the behavioral model of the virtual ideological and political learning environment in order to develop the cognitive decision-making model of the virtual intelligent body. The PageRank algorithm is used to extract the learning habits of students. Learner portraits and learner styles are constructed using the FSLSM model. The real path of integrating red cultural materials into civics education may therefore be accomplished by applying the TF-IDF algorithm based on the learner's style to obtain the key entity that marks the beginning point of the path suggestion. Civics learning difficulty is examined through personalized route analysis of the knowledge point suggestion path and knowledge point learning path. At the same time, students' attention and political learning ability are tested to analyze the effectiveness of the integration of red cultural resources.

2 Modeling of the virtual civic and political learning environment

2.1 Geometric Modeling of Virtual Civics Learning Environment

2.1.1 Solid modeling

The first stage is to create some simple models, such square, cylindrical, and rectangular bodies, using the 3DS MAX program. Based on these fundamental models, we will next use extrusion and patchwork techniques to grow our model and adjust its properties to make it more realistic.

2.1.2 Component paternity adjustments

The geometric modeling technique is depicted in Figure 1. Even if the structural elements of certain complex three-dimensional models have been represented as solids, they are still separate entities that need to have their parent-child connection adjusted in order to be put together as a single, cohesive entity. In the meantime, the structural components' proportions, angles, and locations are changed to make them more realistic.

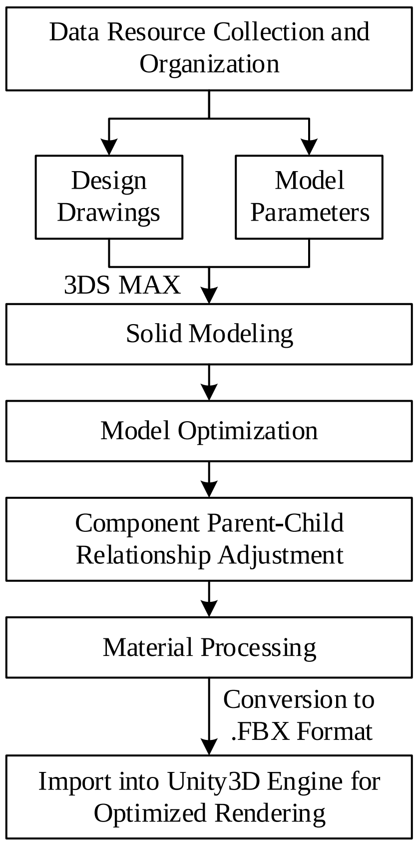

Figure 1: Geometric modeling route

2.1.3 Material handling

There should be an instance where the model is instantiated after the parent-child relationship in the solid modeling has been altered. Every real-world object has a unique substance, and including that material into the 3D model will enhance its realism, which is essential for building a geometric model. Realistic 3D effects may be produced by using several types of materials for each object.

2.1.4 Model optimization

Since the degree of model complexity significantly affects the system's overall efficiency, the 3D objects produced by solid modeling frequently require model optimization. As a result, the model surfaces that connect the surfaces of the three-dimensional objects, three-dimensional vertices, etc., should be eliminated and combined in order to maximize both the number of surfaces and the number of models, improving both the virtual scene load speed and system performance.

2.2 Behavioral Modeling of Virtual Civic Learning Environment

2.2.1 Virtual Intelligent Body Environment Sensing

The visual perceptron of the virtual intelligent body is an essential part of the visual perception of the virtual intelligent body, through which the perceptron can perceive the position, size, shape and other information of the surrounding objects, and then make decisions on appropriate behavioral actions according to its own cognitive model. According to research, the range of the field of view visible to the human eye is a conical area centered on the human eye with a viewing angle of 60°, and Figure 2 shows the visual perception. Only objects that are within the field of view can be seen by the human eye.

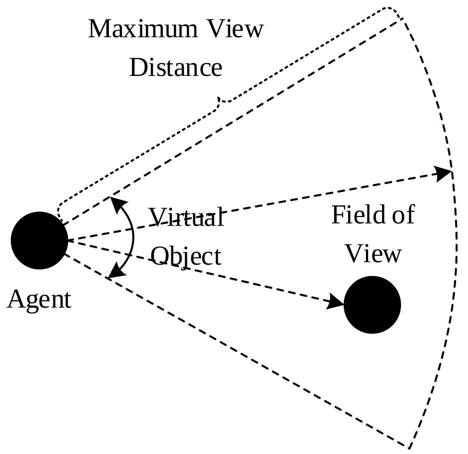

Figure 2: Visual perception

The virtual learning environment is created using Unity3D and the 3D model of the virtual intelligence is imported. In order to make the virtual smart body have human behavior and decision-making, we need to add the “Sight Sensor” script to it, which defines the field of view of the visual sensors. In addition, the “Sight Trigger” script needs to be added to other objects in the virtual environment, so that only the objects carrying the trigger script can be sensed by the virtual smart body.

2.2.2 Cognitive Decision Making in Virtual Intelligentsia

In this paper, FSM is used to build the cognitive decision-making module of the virtual intelligent body, and its real-time nature can provide a reliable guarantee for the rapid response of the virtual intelligent body.

A finite state machine is a mathematical model that consists of states and transitions, as seen in Figure 3, State Transition Diagram. Anything may be described using a finite number of states, which form the set of states that anything passes through at any given moment. Anything undergoes a state shift when it is stimulated by its surroundings.

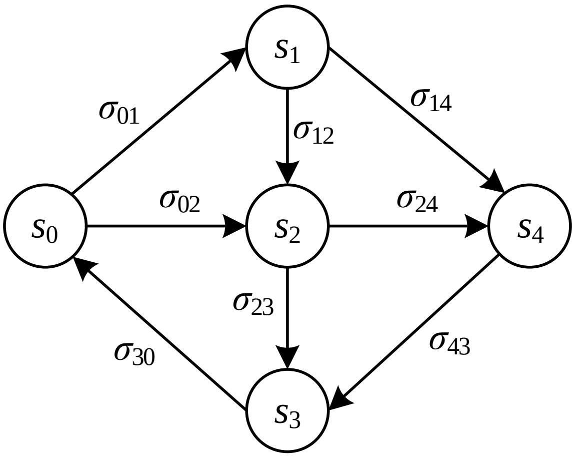

Figure 3: State transition

Every state of a virtual smart body is represented by a node, and the directed weighted edges that link nodes represent the process of changing states and the values that correspond to the information inputs that the machine receives from outside sources. The FSM also incorporates the idea of a "dead state," which is the capacity to move to and from a specific state when no state is accessible in the switch's state transition diagram. The FSM enters the "dead state" if there isn't a state available for a switch in the state transition diagram. Equation (1) may be used to construct a finite state machine mathematically.

$$M = \left(Q, s_0, X, Y, \delta, F\right) \tag{1}$$

where Q represents a finite set of states, s_0 represents the initial state of a finite set of states, which is one of the finite sets, X is the effect of external stimuli, which is a finite set of inputs, Y represents the transfer of states induced by the inputs, which is also one of the finite sets of states, δ is the state transfer function controlling the transfer of states, which leads to state occurring $Q \times X \to Q$, F is the final state set, also one of them.

In this paper, we implement the FSM framework through Unity3D's animation state machine Animator Controller component. Each Animator Controller component comes with three states: Entry, AnyState, and Exit states, which correspond to the initial, intermediate, and final states in the state machine. In addition, the state switching parameter can be added to control the state switching, in this way the state transfer of the finite state machine can be realized.

2.3 Physical modeling of virtual civic learning environment

Both the physical model utilized in the virtual learning environment and the experimental system in the experiment teaching are becoming more complex due to the ongoing development of the teaching environment. Additionally, the application field is being expanded. Therefore, it must be necessary to do dynamics-based physical modeling of the experimental model in order to continue developing the virtual learning environment system.

This will make it possible to simulate the objects' behaviors effectively, improving the learning environment system's overall interactivity.

Equations (2) and (3) illustrate how the equations of motion of the inverted pendulum system may be determined by examining the force acting on the cart:

$$\left(M+m\right)\ddot{x}+b\dot{x}+ml\ddot{\theta}\cos\theta-ml\dot{\theta}^{2}\sin\theta=F \tag{2}$$

$$\left(I+ml^{2}\right)\ddot{\theta}+mgl\sin\theta=-ml\ddot{x}\cos\theta \tag{3}$$

The system's state variables are the cart displacement, cart velocity, pendulum angle, and pendulum angular velocity. Equations (2) and (3) are transformed into the system's state space expression; refer to Eq. (4):

$$\begin{gathered}\begin{bmatrix}\dot{x}\\ \ddot{x}\\ \dot{\theta}\\ \ddot{\theta}\end{bmatrix}=\begin{bmatrix}0 & 1 & 0 & 0\\ 0 & -\dfrac{(I+ml^{2})b}{I(M+m)+Mml^{2}} & \dfrac{m^{2}gl^{2}}{I(M+m)+Mml^{2}} & 0\\ 0 & 0 & 0 & 1\\ 0 & -\dfrac{mlb}{I(M+m)+Mml^{2}} & \dfrac{mgl(M+m)}{I(M+m)+Mml^{2}} & 0\end{bmatrix}\begin{bmatrix}x\\ \dot{x}\\ \theta\\ \dot{\theta}\end{bmatrix}\\ +\begin{bmatrix}0\\ \dfrac{I+ml^{2}}{I(M+m)+Mml^{2}}\\ 0\\ \dfrac{ml}{I(M+m)+Mml^{2}}\end{bmatrix}u\\ y=\begin{bmatrix}x\\ \theta\end{bmatrix}=\begin{bmatrix}1 & 0 & 0 & 0\\ 0 & 0 & 1 & 0\end{bmatrix}\begin{bmatrix}x\\ \dot{x}\\ \theta\\ \dot{\theta}\end{bmatrix}+\begin{bmatrix}0\\ 0\end{bmatrix}u\end{gathered} \tag{4}$$

where u is used to represent the force F of the cart, and also for writing convenience, let $\dot{x}=dx/dt,\ddot{x}=d^{2}x/dt$, $\dot{\theta}=d\theta/dt,\ddot{\theta}=d^{2}\theta/dt$.

Bringing each parameter into Eq. (4), the state space expression of the actual system can be obtained, see Eq. (5):

$$\begin{aligned}
&\begin{bmatrix} \dot{x} \\ \ddot{x} \\ \dot{\theta} \\ \ddot{\theta} \end{bmatrix} = \begin{bmatrix} 0 & 1 & 0 & 0 \\ 0 & -0.0883 & 0.6293 & 0 \\ 0 & 0 & 0 & 1 \\ 0 & -0.2357 & 27.8285 & 0 \end{bmatrix} \begin{bmatrix} x \\ \dot{x} \\ \theta \\ \dot{\theta} \end{bmatrix} + \begin{bmatrix} 0 \\ 0.8832 \\ 0 \\ 2.3566 \end{bmatrix} u \\
&y = \begin{bmatrix} x \\ \theta \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} x \\ \dot{x} \\ \theta \\ \dot{\theta} \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \end{bmatrix} u
\end{aligned} \tag{5}$$

The linear-quadratic optimum control technique (LQR) is one of several control methods that may be used to stabilize inverted pendulum systems, which are the most traditional control objects in the field of automated control. Assume for the moment that a linear system's state equation is:

$$\begin{cases} \dot{x}(t) = Ax(t) + Bu(t) \\ y(t) = Cx(t) + Du(t) \end{cases} \tag{6}$$

Typically, the quadratic performance indicator function is selected as follows:

$$J = \frac{1}{2}\int_0^\infty x^T(t)Qx(t) + u^T(t)Ru(t)dt \tag{7}$$

where $x(t)$ is the state variable, Q is the semipositive definite weighting matrix of the state variable, $u(t)$ is the control input variable, R is the positive definite weighting matrix of the control input, and J is the performance index function. Optimal control aims to minimize the performance index function. The idea of minimal values may be used to determine the system's optimal control inputs, as demonstrated by Equation (8):

$$u^*(t) = -Kx(t) = -R^{-1}B^T P(t)x(t) \tag{8}$$

$$\dot{P}(t) = -P(t)A - A^T P(t) + P(t)BR^{-1}B^T P(t) - Q = 0 \tag{9}$$

K is the feedback gain matrix and $P(t)$ is the solution of the Riccati differential equation Eq. (9). For solving the linear quadratic optimal control problem, the following steps are generally taken to operate.

Based on the above steps, the modeling of the virtual Civics learning environment is completed.VR technology, on the other hand, superimposes historical information and digital content in the real environment, so that the traditional cultural relics, ruins, and memorials are revitalized with new educational vitality. This model breaks the time and space limitations, reduces the cost of education, enhances the attractiveness and infectiousness of red cultural education, effectively promotes emotional resonance and value recognition, and opens up a new way for the inheritance of red genes.

3 Generation of Learning Paths for Integrating Red Culture into Civic and Political Education

3.1 Learning path recommendation

3.1.1 PageRank algorithm

The PR of a web page is defined as the ratio of the number of users staying on the web page N_i at a given moment to the total number of users. When the number of users is large enough, then $PR(N_i)$, $N_i \in G$ is stable and unique, i.e., each $PR(N_i)$ converges. After converting the network graph into a directed graph as described above, if each web page is independent of each other, the convergence of only one part of the web page is considered, which obviously will not affect the convergence of the rest of the web page. If the weights of the edges of each relation are taken as the PR values passed by the web pages, then with respect to any vertex, the sum of the weights passed outward from that point must be 1.

Each vertex will its own PR value, equally distributed to all outward links to the node, the remaining nodes will absorb all the nodes pointing to their own nodes assigned PR value, and thus complete their own update and recursive this operation, until all nodes are completed, the end of the round of the cycle. The PR values of all nodes within the connected graph keep the total number of PR values conserved during the circulation process. Even if there exists a node with an entry degree of 0, the PR value of this class of points is transferred to the external connectivity point, and the total amount of internal PR values remains conserved.

$PR(N_A)$ denotes the PR value of node A, S_A denotes the set of nodes pointing to node A, and the out-degree value of each point in the set of nodes N is $O(N)$, so the basic idea of the Page Rank algorithm can be expressed by formula (10):

$$PR(N_A) = \sum_{N \in S_A} PR(N) / O(N) \tag{10}$$

According to Equation (10), the PR value will be transferred according to the out-degree of the current node after the average distribution, when the web page is linked by multiple high-quality web pages, naturally, it will have a higher PR value, and its importance in the directed graph of that network is higher, and the PR value can be transferred normally only in the connected graph. When there exists a node with out degree 0 in the connected graph, i.e., there is no outward link, then after a finite number of iterative calculations, the rest of the vertices PR values within this connected graph except for this type of points are all 0. The two nodes of N_B and N_C. Since there is no external transfer of PR values, the flow of the rest of the points in each round of iteration is relatively fixed, and eventually converges to 0. If there are points with an in/out degree of 0, there will be a class leakage or sinking phenomenon due to the cessation of transfer of PR values, which ultimately leads to the fact that the PR values within the connected graph are all transferred into the nodes similar to N_B, whereas the nodes of the class N_C will be converged to 0 due to the absence of PR values are transferred to the rest of the nodes in the connectivity graph in order to prevent the above phenomenon from occurring, avoiding the PR values from being completely absorbed, and Page by adding a decay factor d, which can be regarded as the probability that a user stays on a certain page and terminates the skip browsing as d, while the rest of the nodes continue to be assigned PR values. The modified formula (11) is as follows:

$$PR(N_A) = \frac{1-d}{O(N_A)} + d * \sum_{N \in S_A} PR(N) / O(N) \tag{11}$$

3.1.2 Learner profiles

A learning style is a fairly consistent trait that students exhibit throughout the learning process, which includes different aspects of how students perceive, acquire, process, and comprehend information. Applying the FSLSM model to create a learner profile improves users' impression of tailored resource suggestions, according to an evaluation of the profile modeling technique and its implementations.

3.1.3 Keyword of Interest Entity Extraction

Interest keyword extraction as the first basis of route recommendation will improve the profile experience and boost the accuracy of the initial basis of interest suggestion and path recommendation based on the acquisition of the learning style. The first step in the interest keyword extraction process is named entity recognition, which entails removing entities from either structured or unstructured datasets. An entity is a crucial information carrier that could be anything from a person's name to a location or even an idea. Early manual extraction methods utilizing string matching gave way to more modern automated extraction methods using natural language processing (NLP), and today named entity recognition in the knowledge graph even uses deep learning.

The TF-IDF algorithm, a popular technique for extracting keywords, determines the weight of each word in the text by computing word frequency (TF) and inverse document frequency (IDF). The frequency of a word is equal to how frequently it appears in the text. To some extent, the frequency of a word's presence can be positively correlated with its significance; that is, the more frequently a word appears, the more significant it is. The inverse document frequency, on the other hand, is the frequency with which the word appears in the corpus; in contrast to the word frequency, the greater the inverse document frequency, the more widespread the word is, i.e., the less likely it is to be a keyword. The calculation formula contains two parts:

$$TF = \frac{f_{i,j}}{\sum_k f_{k,j}} \tag{12}$$

where $f_{i,j}$ denotes the number of occurrences of the word w_i in the text d_j, and TF is the weight of w_i in the text d_j:

$$IDF = \lg \frac{|D|}{1 + \left|\left\{ j : w_i \in d_j \right\}\right|} \tag{13}$$

where D is the total amount of corpus text, $\left\{ j : w_i \in d_j \right\}$ denotes the number of texts in which w_i appears in the corpus. Combining the above two, the final formula is shown in equation (14):

$$TF - IDF(w_i) = TF(w_i) * IDF(w_i) = \frac{f_{i,j}}{\sum_k f_{k,j}} * \lg \frac{|D|}{1 + \left|\left\{ j : w_i \in d_j \right\}\right|} \tag{14}$$

Each word in the recognition body is processed and analyzed to determine its TF-IDF value, which serves as the foundation for keyword selection.

The forgetting gate's functionality determines whether or not to forget. Data input consists of the input at the current time point, the memory cell state from the previous time step, and the hidden layer state from the previous time step, and the output is outputted by the sigmod activation function with $f_t = 1$ or 0, the former indicating complete retention while the latter indicating complete forgetting. Its forward propagation formula is:

$$f_t = \sigma\left(W_{xf} x_t + W_{hf} h_{t-1} + W_{cf} c_{t-1} + b_f\right) \tag{15}$$

To determine whether or not information must be kept, input gates are utilized. The propagation formula is as follows, and the same activation function is employed:

$$i_t = \sigma\left(W_{xi} x_t + W_{hi} h_{t-1} + W_{ci} c_{t-1} + b_i\right) \tag{16}$$

$i_t = 0$ or 1, $i_t = 0$ means that the current information is discarded, otherwise it is retained, and the information to be added depends on the input at the current time with the state of the hidden layer at the previous moment, and the information to be added is denoted as z_t, and the formula is:

$$z_t = \tanh\left(W_{xc} x_t + W_{hc} h_{t-1} + b_c\right) \tag{17}$$

These memory cells are used to store information by using the following formula to update memory cells in accordance with the need to store both new and old information:

$$c_t = f_t c_{t-1} + i_t z_t \tag{18}$$

The output gate determines the output of the current message, for the moment t, if $o_t = 0$ it means that the current layer is not output, and if $o_t = 1$, it means that it is output, the formula is as follows:

$$o_t = \tanh\left(W_{xo} x_t + W_{ho} h_{t-1} + W_{co} c_t + b_o\right) \tag{19}$$

The content to be output, h_t, is determined by the information in the memory cell at the moment of t normalized by the hyperbolic tangent function together with the output gate, Eq:

$$h_t = o_t \tanh\left(c_t\right) \tag{20}$$

3.2 Path generation

3.2.1 Knowledge Mapping of Civics Programs

The connections between the nodes—such as the degree of difficulty of the knowledge points, the degree of importance, and the weight determination of the relationships, play a critical role in learning more about the design of an optimal learning path planning approach according to the characteristics of the knowledge points. As a result, the features and relationships of knowledge points are thoroughly taken into account in the knowledge graph while designing the automatic development of learning routes. The relationships between the knowledge points often fall into two categories.

3.2.2 Generation algorithms

The hierarchy is used to order the information points according to their significance, beginning with the most crucial and working down to the least crucial. Additionally, it is based on the degree of difficulty, going from the easiest to the worst, and then taking into account the topological and centrality levels in increasing order.

The following are the feature values of knowledge point attributes are calculated:

(1) Knowledge point importance: using the TF-IDF keyword extraction algorithm, i.e., Equation (14), the red culture text resources are processed to obtain the knowledge point set and knowledge point importance.

(2) Knowledge point difficulty: The test scores of all students studying the same material are used to determine the values that indicate the degree of difficulty of a knowledge point. The formula (21) is used to calculate these values:

$$Diff(V_i) = \omega 1 \times Sco(V_i) + \omega 2 \times Rep(V_i) + \omega 3 \times Com(V_i) \tag{21}$$

where: $\omega 1, \omega 2, \omega 3$ are the weights of the input parameters, $Sco(v_i)$, $Rep(v_i)$, and $Com(v_i)$ are the average test scores, the average number of repetitions of the study, and the average number of comments of the knowledge point V_i, respectively. The larger value of $Diff(V_i)$ represents that the knowledge point V_i is more difficult to master. With reference to the course requirements and based on the $Diff(V_i)$ value, the knowledge points are categorized into four levels: Knowledge, Understanding, Mastery and Application:

$$Sco(i) = \frac{\sum_{j=1}^{N_i^h} scoij}{N_i^h} \tag{22}$$

$$Rep(i) = \frac{\sum_{j=1}^{N_i^h} repij}{N_i^h} \tag{23}$$

$$Com(i) = \frac{\sum_{j=1}^{N_i^h} comij}{N_i^h} \tag{24}$$

In Eqs. (22), (23) and (24), N_i^h is the total number of learners learning the i th knowledge point, and $scoij$, $repij$ and $comij$ are the test scores, number of repetitions, and number of comments made by the j th learner on the i th knowledge point, respectively.

(3) Knowledge point centrality: Although there isn't a single definition for centrality, it's commonly understood to mean nodes having strongly interwoven linkages. According to the knowledge graph's structure and the learning process, a knowledge point's centrality is determined by how much effect it has inside the knowledge graph. Equation (25) defines the

in-degrees and out-degrees of knowledge points. Centrality is determined by calculating the ratio of the in-degrees and out-degrees of the knowledge point; the higher the ratio, the greater the impact of a knowledge point on subsequent learning processes.

$$\begin{cases} \text{In-degree：Knowledge Point } V_i \\ \text{First-Order Predecessor Knowledge Points} \\ \text{Out-degree：Knowledge Point } V_i \\ \text{First-Order Successor Knowledge Points} \end{cases} \tag{25}$$

The degree of the knowledge point V_i is divided into in-degree and out-degree, therefore, the center degree of the knowledge point is calculated as in equation (26):

$$C(v_i) = \begin{cases} 1,\ if \left(\|Suc(V_i)\| = 0\right) or \left(\|\Pr e(V_i)\| = 0\right) \\ \|Suc(V_i)\| \Big/ \|\Pr e(V_i)\|,\ others \end{cases} \tag{26}$$

where: $C(V_i)$ is the ratio of in-degree to out-degree of bit node V_i, $Pre(V_i)$ is the set of first-order precursor knowledge points of knowledge point V_i, and $Suc(V_i)$ is the set of first-order successor knowledge points of knowledge point V_i.

(4) Knowledge point topology level: The depth of the knowledge point's location in the graph is described by this level; the greater the depth, the more prior information the knowledge point must master. The knowledge graph's structural architecture allows for the direct determination of the topological level of knowledge points.

The above attribute values are utilized to calculate the knowledge point ranking index W_{kpi}, as in Equation (27):

$$W_{kpi} = \omega_{imp} \times Imp_{kpi} + \omega_{diff} \times Diff_{kpi} + \omega_{cent} \times Cent_{kpi} + \omega_{tp} \times Tp_{kpi} \tag{27}$$

where: Imp_{kpi}, $Diff_{kpi}$, $Cent_{kpi}$, and Tp_{kpi} are the importance, difficulty, centrality, and topological hierarchy of the knowledge point kpi, respectively, and $\omega_{imp}, \omega_{diff}, \omega_{cent}, \omega_{tp}$ are manually assigned attribute weight values.

The knowledge graph is created based on the many kinds of links that exist between the knowledge points as well as their significance, difficulty, centrality, and topological hierarchy. Based on the topological sorting algorithm, starting from the starting knowledge point, access its first-order neighboring knowledge points with the principle of depth-first traversal, and after traversing all the knowledge points on a branch, select the unvisited knowledge points in another branch, and repeat the above steps until all the knowledge points in the graph are traversed. The flow of the generic learning path automatic generation algorithm is shown in Fig. 4.

(1) A collection of knowledge points to be sorted KG, all knowledge points in the knowledge graph are listed as a collection of knowledge points to be sorted in this study, and, for subsequent analysis and computation, an initial knowledge point KP_0 is manually specified in this study.

(2) The list of knowledge points and relation triples L, which can be directly exported

from the Neo4j database. The record information of the list L is $\left(KP_m, R, KP_n\right)$, which indicates that the relationship between knowledge point KP_m and KP_n is R.

(3) Knowledge point importance, difficulty, centrality and topological hierarchy attribute feature data Imp_{kpi}, $Diff_{kpi}$, $Cent_{kpi}$, Tp_{kpi}, as well as knowledge point ranking index W_{kpi}.

(4) Combining the knowledge graph and knowledge point attribute feature data, the topological sorting algorithm is utilized to generate the learning path.

Finally, the output of the algorithm is the generic learning path $Path_{kpi}$ with $Path_{kpi} = \left(KP_1, KP_2, \cdots, KP_n\right)$.

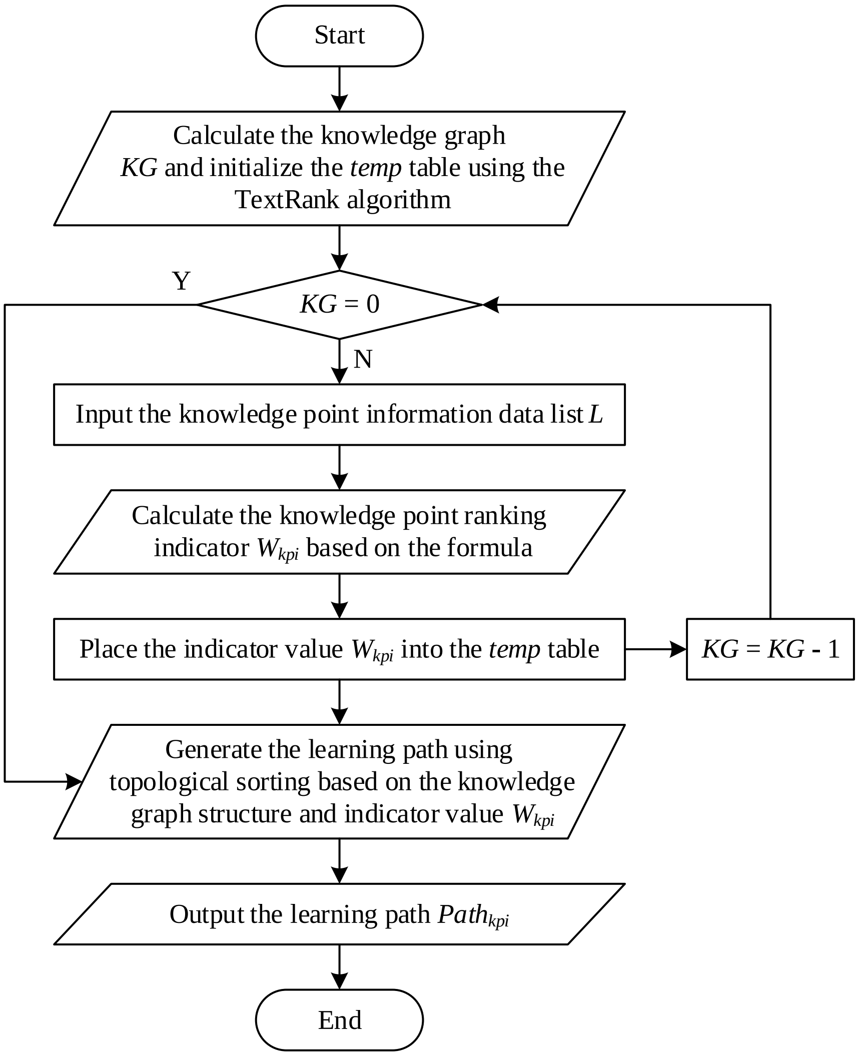

Figure 4: Flowchart of the general learning path generation algorithm

The model accurately portrays students' cognitive characteristics, learning styles, and value orientations through the construction of multi-dimensional learner profiles. It intelligently adjusts the content difficulty and presentation mode according to the learning progress. The course recommendation engine granulates red cultural resources, reorganizes them by knowledge points, ability dimensions and value elements, and provides customized content packages for different learners.

4 Analysis of the effect of integrating red culture into civic learning

4.1 Personalized Learning Path Analysis

4.1.1 Personalized Analysis of Knowledge Point Test Paths

In the knowledge point test session, each knowledge point corresponds to two practice questions, if all the students answer correctly, it is regarded as the knowledge point mastery, on the contrary, if any one of the two questions is answered incorrectly, it is regarded as the knowledge point is not mastered, and if there is an error in the first question in the two exercises corresponding to the knowledge point, then the system will no longer push the second exercise and directly into the test of the next knowledge point, the answers of the three students in the test session. The number of questions answered by the three students in the test session is shown in Table 1. Through the data in the table, we can see that the number of questions answered by student A is slightly more than that of the two students, B and C, because student A only made a mistake in the first question in the knowledge point T3, while students B and C made a mistake in the first question in the knowledge points T3, T5, and T7, and the scores of the three students totaled to 15, 13, and 13 points respectively. It shows that these two knowledge points should be the students' easy points in this section.

Table 1: The number of questions answered by three students in the test session

Student	T1	T2	T3	T4	T5	T6	T7	T8	Total
A	2	2	1	2	2	2	2	2	15
B	2	2	1	2	1	2	1	2	13
C	2	2	1	2	1	2	1	2	13

The difficulty value of the test questions recommended by the model was found to be between 40 and 80 marks, with the majority of the questions being moderately tough, according to the summary of the three students' test question difficulties. The test question difficulty values were divided into two intervals, and Table 2 was used to determine the percentage of test question difficulty values of the three students in each interval in order to assess whether the test questions that the model pushed to students in different grades differed significantly. It can be observed that the test question difficulty value of Student A was somewhat higher compared to those of the other two students, indicating a certain level of personalization. The test question difficulty value of the test questions pushed to Student A was somewhat higher compared to those of the other two students, showing a certain level of personalization, and the probability that the difficulty interval belongs to the range of 60 to 80 marks was 53.3%. However, the two students of B and C, the proportion of the difficulty value of the push questions is completely consistent without distinction, mainly fall in the 40 to 60 points interval, the probability of both 66.80%, indicating that the model for learning in the middle and upper levels of the students' differentiation to be a little stronger.

Table 2: Summary of the difficulty ratio of the three students' answers in the test

The difficulty range of student test questions	40 to 60 points	60 to 80 points
A	46.70%	53.30%
B	66.80%	33.20%
C	66.80%	33.20%

4.1.2 Learning path analysis of knowledge points

Following the test, the model pushes the teaching material for students who have not mastered the knowledge points because the three students' test results differ and the system determines their ungraspable knowledge points differently. As a result, the three students' learning paths differ, as do their levels of learning content and the frequency of learning statistics, Table 3 for the learning of the three students' knowledge points, the learning content of the three students A students contains two knowledge points respectively Learned 2 times and 1 time, a total of 3 times, B students learned 6 knowledge points, including T6 knowledge learned 3 times, T3 learned 2 times the rest of the knowledge points to learn once, C students learned 4 knowledge points, including T2 learned 3 times, there is a knowledge point of the remaining three knowledge points to learn 1 time, which shows that the model is able to make a judgment on the knowledge mastery of the students and according to the cognitive situation of the different students to arrange the corresponding learning paths, reflecting the characteristics of the model personalized teaching.

Table 3: Three students learning information

	T1	T2	T3	T4	T5	T6	T7	T8	Total
A	0	2	0	0	0	1	0	0	3
B	1	1	2	1	1	3	0	0	9
C	1	3	1	0	0	1	0	0	6

4.1.3 Learning difficulty

In addition to the quantity of practice problems students complete, the model can be tailored to the learners' learning circumstances so that the difficulty level of the questions corresponds to the learners' level of study. This is the realization of personalized instruction, as both difficult and easy questions are inappropriate to pique the learners' interest in learning. The author categorized the results into four intervals and gathered statistics regarding the distribution of the difficulty value of the exercises completed by the three students in this lesson because the tracking survey of various levels of students' learning process revealed that the three students' exercises, pushed by the model, had difficulty values between 0 and 80 points. In order to gather statistics regarding the distribution of the difficulty value of the exercises completed by the three students in this lesson, the author divided it into four intervals based on the tracking survey of various levels of students' learning process, which revealed that the exercises pushed by the model for the three students ranged from 0 to 80 points. Figure 5's proportion % may be used to determine the entire workouts' difficulty value push. The system pushes the difficulty value of exercises completed by student A as both high and low value exercises and middle-score exercises as supplements. Exercises completed by student A with difficulty values ranging from 20–40 points and 60–80 points account for a proportion as high as 35%, while 40–60 points take up 20% and the minimum proportion of 10% of 0–20 points. Regarding student C's exercises, the difficulty values are primarily medium-score and high-score, accounting for 40% and 30% of the total. This could be the result of student C repeating the study more frequently and pushing the incorrect questions from the first study session into the exercise questions of the re-learning. The difficulty value of this type of exercise question typically falls between the middle and high level, and student C made mistakes when answering the questions the first time and mastered them in the repeated study. The difficulty score of these exercises generally belongs to the medium-high level, and student C made mistakes in the first time he answered them and mastered them in the repeated learning, which led to a higher proportion of high-difficulty score exercises in student C.

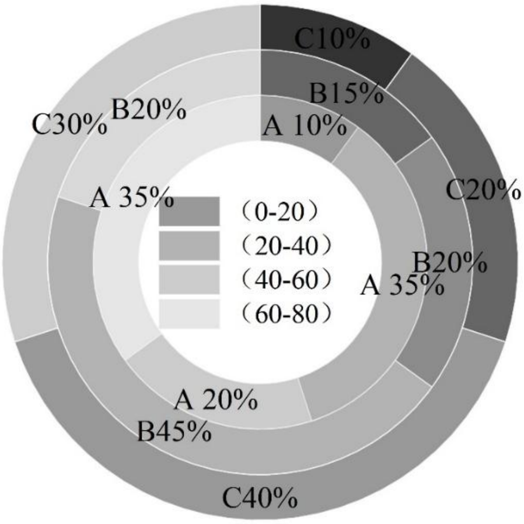

Figure 5: The overall difficulty is the ratio of the problem

Additionally, it was discovered from this study article that all three students have studied and practiced the knowledge points "T2" and "T6" in order to ascertain whether they respond differently to the same information point for the same push question that the model poses to them. In order to investigate whether there is a difference in the difficulty distribution of pushing questions for the same knowledge point among different students, the distribution of the difficulty of pushing questions for the same knowledge point has been statistically analyzed. For the T2 knowledge point, the difficulty of the push questions of student A is mainly 60-80 points, with 42% of the difficulty ratio, while student B is mainly 40-60 points, with 48% of the difficulty ratio. The difficulty proportion of C students is more scattered, with 0~20 and 20~40 each accounting for 28%. The difficulty ratio of the above exercises is in line with the learning situation of the three students, reflecting the personalized Civics teaching effect of the model. Figure 7 shows the difficulty ratio of the T6 knowledge point model push questions. From the figure, it can be seen that the difficulty of push questions of B students is mainly 40~60 points, accounting for 60%. Students A and C scored mainly 20 to 40 points, accounting for 60% and 50% respectively. This may be due to the fact that the model pushes the exercises according to the increasing difficulty, and if there is an error, the difficulty of the exercises will be lowered. A student made an error in the third exercise corresponding to this knowledge point, so the system lowered the difficulty of the exercises, resulting in A student's overall low difficulty of the exercises in this knowledge point.

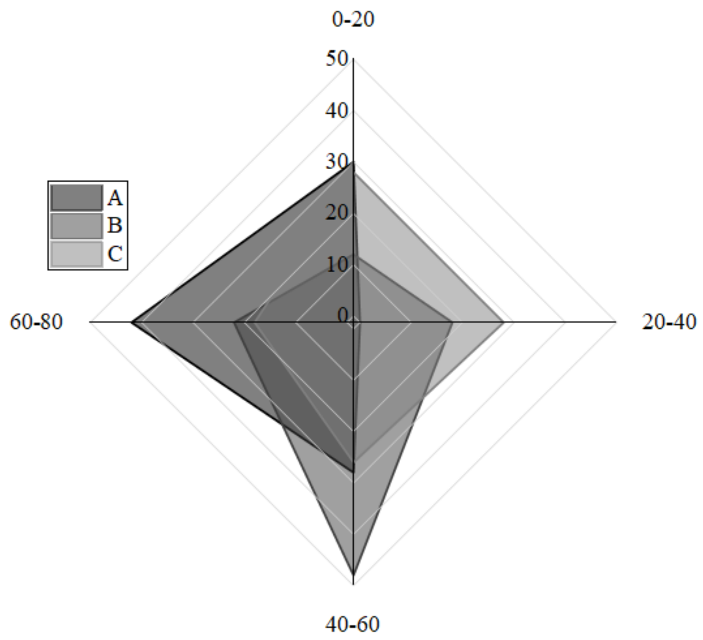

Figure 6: The proportion of difficulty in T2 knowledge point model push questions

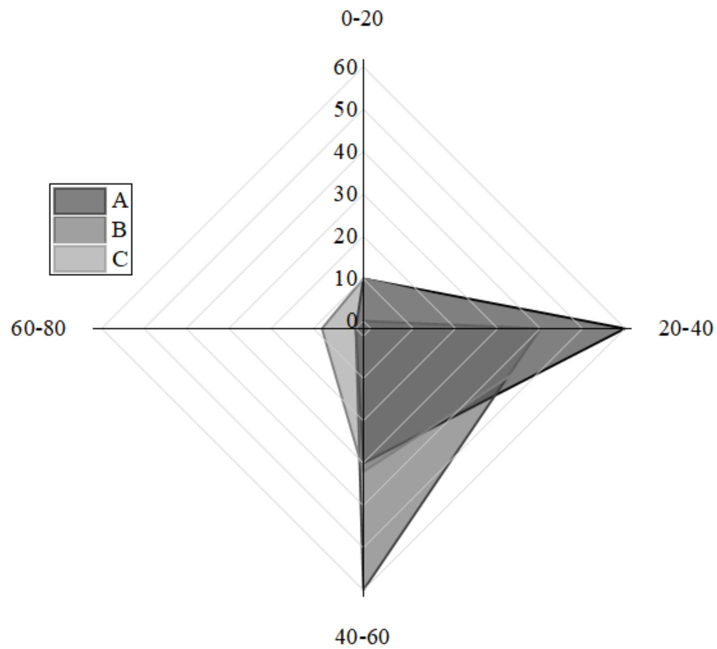

Figure 7: The proportion of difficulty in the T6 knowledge point model push questions

The distribution of the exercises' difficulty values for the three learners shows that the system has some degree of adaptability in how the exercises are delivered; as a result, it will suitably supply activities based on the learners' responses. Nonetheless, it is clear that various learners' matching accuracy is low. This method more closely aligns with learners at the intermediate level.

4.2 Tests on the level of knowledge and competence

4.2.1 Analysis of students' attention levels

To confirm the scientific validity of the findings of the experiment on the incorporation of red culture into college students' civic education, civic education is conducted in a virtual civic learning environment using the learning path generating model. The experimental class uses the aforementioned techniques for civic and political education, whereas the control class uses conventional classroom instruction.

Figure 8 shows the frequency analysis, and the questions from Q1 to Q5 are, respectively, the degree of memorization of knowledge points, the degree of completion of Civics assignments, the degree of inheritance of red culture, the degree of acceptance of the Civics classroom, and the degree of attention to the game of integrating red culture into the Civics classroom. The control class in the students' attention level effect is not ideal, manifested in too much attention to classroom games, classroom teaching can not remember the knowledge taught by the teacher, even the homework can not insist on completing, the number of people reached were 18, 30, 35, respectively, and the experimental class data is relatively ideal, except for the game attention level, the number of people reached for all the questions are more than 35 people. It proves that the attention level improvement study is beginning to be effective.

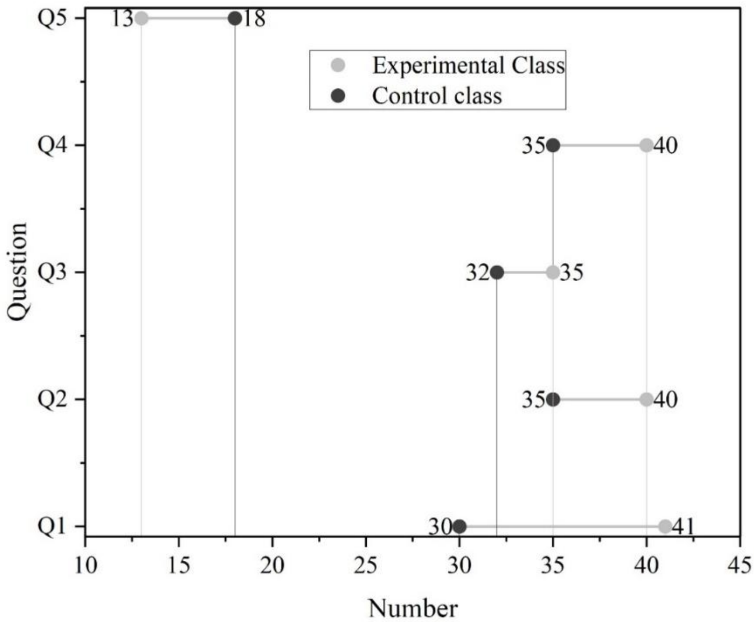

Figure 8: Frequency analysis

4.2.2 Evaluation of Civic Learning Competencies

We further examine and investigate the impact of red cultural materials on students' attention level of civics learning in a virtual reality setting using the assessment level of students' final civics learning power. The learning capacity assessment is displayed in Table 4, and the excellence rate is the ratio of A grades to all pupils. The experimental class's average score, the number of A-level students, and the excellence rate are much greater than those of the control class (93.24 points, 42 students, and 93.33%), respectively, indicating that the use of the learning path generation model and the civic politics learning in the virtual civic politics learning environment make the red culture integrated into the classroom of college students' civic politics education and the experimental effect is good.

Table 4: Evaluation of learning ability

Class	Control class	Experimental Class
Real number	45	45
Reference number	45	45
Total score	4038.3	4195.8
Average score	89.74	93.24
A-level	35	42
B-level	8	3
C-level	2	0
D-level	0	0
Excellence rate	77.78%	93.33%
Rate of conformity	100	100

5 Conclusion

This article describes how virtual modeling technology was used to accomplish the modeling process of the civics learning environment. In order to expedite the loading of the virtual scene, optimization of the 3D objects is carried out after resolving difficulties such as parent-child connections and materials. To replicate the virtual physical environment, a virtual intelligent cognitive decision making module based on the FSM approach will be developed using behavioral modeling of ideological and political learning environments. In the meantime, the TF-IDF keyword extraction algorithm will be used to process the textualized red cultural materials in order to generate the knowledge point set and significance level needed to integrate them into the Civic and Political Learning Path.

The personalized analysis of the model's knowledge point test paths showed that the scores of the three students under test totaled 15, 13, and 13 points respectively.Students B and C made the first error in the knowledge points of T3, T5, and T7, which indicated that these two knowledge points should be the students' easy-to-errors in this section of knowledge. The outcomes of the experiment on incorporating red culture into college students' civic and political education were verified through a controlled experiment. The research on improving the level of attention of civics learning based on the learning path generating model and in the virtual Civic Learning Environment was initially successful, as evidenced by the fact that over 35 students in the experimental group reached the degree of memorization of the knowledge points of civics learning, the degree of completion of civics assignments, the degree of inheritance of red culture, and the degree of acceptance of the civics classroom.

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