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Online art teaching course design based on 5g technology and big data assistance and its impact on instructional delivery

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ABSTRACT

This paper constructs the SAM agile iterative model according to the direction of online art course design, firstly by collecting art teaching related information and initiating the cognitive system of art teaching, and then entering into the iterative design phase to accomplish the development goal of the online art course incrementally through continuous iteration. Finally, after the double iteration phase, the software process enters the delivery phase to complete the design of the online art teaching course. The effect of the online art teaching course and its impact on delivery are analyzed in conjunction with the dynamic key-value memory network model based on the forgetting curve. The results of the memorization ability of art knowledge experiments in the pre-test have a mean value of 35.259, and the post-test has a mean value of 53.1254, while the Sig value of the paired test is 0.000, 0.000<0.05, which indicates that the effect of using the online course for art learning based on the Ebbinghaus forgetting curve is more significant on the learning of art knowledge than other applications. The regression results of the full sample model showed that overall instructors' use of big data aids for online art instruction significantly affects instructional delivery, t=1.245, P=0<0.05, which is significantly positive at the 1% level, indicating that the more adequate the use of these instructional methods, the higher the probability that students will rate their satisfaction with the instructional delivery.

Keywords: agile iterative model of SAM, double iterative stage, Ebbinghaus forgetting curve, dynamic key-value memory network, online art teaching

1. Introduction

Art education is an indispensable part of basic education, and has a particularly prominent impact on students' aesthetic cultivation and emotional education [1-2]. Times are advancing, science and

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technology is developing, education as a particularly important part of the development of the times, is bound to synchronize with the times, or even ahead of the development. Obviously, the traditional art teaching has not been able to fully meet the times, must be implemented in all aspects of the "teacher's teaching and student learning, as well as the school education concepts and models", these changes in education bit by bit, the reform of art education to the end [3-6].

In the distance open education environment, art teaching has the support of modern Internet technology, virtual classroom platforms and online resource libraries. Art education is taught with the help of the Internet, which not only breaks through the geographical limitations, but also greatly enriches the teaching resources and methods [7]. On the one hand, modern Internet technology provides rich multimedia support and optimizes the effect of remote art teaching [8]. Relying on the wide application of 5G communication technology, images, videos and other visual elements of art teaching can meticulously display every detail of art works with the help of high-definition videos, interactive images and 3D simulation tools on network platforms [9-11]. On the other hand, big data technology enhances the interactivity and participation of teaching [12]. Unlike face-to-face communication in traditional art teaching, in distance learning environments, teachers using big data analytics can obtain students' learning feedback in real time and utilize tools such as online forums and video conferencing for targeted teaching [13-15].

Literature [16] studied the construction of video resource sharing platform under the 5G network environment, the development of communication technology promotes the creation of diversified teaching scenarios, and the demand and positioning of teaching with video as a carrier appear widely, and this is the basis for the formation of a unique art teaching course design. Literature [17] points out that the digital teaching mode of art and painting courses has high requirements for the transmission of audio and video, and therefore proposes an art and painting teaching assistance system based on edge cloud and mobile assistive devices, which helps to enhance the teaching interaction and instant feedback between teachers and students in online courses, and improves the teaching effect of art courses. Literature [18] analyzes the optimization direction of the teaching mode of the art design profession under the 5G network environment, which can use educational information technology to upgrade and adjust the art art design classroom, and promote the development of teaching methods in the direction of digitization, intelligence, and networking, with the aim of promoting the teaching effect to be further improved. Literature [19] integrates adaptive genetic algorithm into the comprehensive education teaching system of art and design with browser server (B/S) architecture as the core, which not only simplifies the teaching management process, but also facilitates the communication between teachers and students, and effectively improves the poor performance enhancement effect and low throughput of the system that exists in the traditional education system. Literature [20] explored the best method of teaching remote skills in art and painting education, compared to offline painting courses, participants in online courses can not view the physical space in which the drawn image exists from multiple perspectives, and technology is needed to make adjustments to the teaching task, providing a new perspective for the development of online art education. Literature [21] examined the impact of digital tools on the learning of drawing knowledge and skills of students at different drawing levels, and empirical investigations found that digital drawing tools significantly improved the drawing skills of low- and middle-performing students, providing some insights into the creation and implementation of an innovative digital drawing program.

Based on the current situation of online art and design teaching courses, this paper proposes the direction of online art teaching course design. Using the SAM agile iterative model, the design and development of an online art teaching course assisted by big data is completed through the preparation phase, iterative design phase, and delivery phase. Aiming at the phenomenon of "forgetting" that occurs in the process of students' art learning, the SAM Agile Iterative Model was applied to the design and development of the online art teaching course. Combining the forgetting curve and the dynamic key-value memory network, we adopt the fitted power function model as the basic model of the forgetting curve. The model is divided into “reading process” and “writing process”, and the forgetting curve is combined with the “reading process” to obtain the dynamic key-value memory network model based on the forgetting curve. Empirical experiments were conducted to compare the memory of art knowledge before and after using the online art teaching course designed in this study. Based on big data technology, the assessment feedback of the art course was evaluated, and the impact of big data assistance on the delivery of art teaching was investigated through regression analysis.

2. Online art course design

2.1. Online art course design path

2.1.1. Online art and design education programs. In the strict sense, the curriculum of higher education refers to the sum of all teaching subjects and their purposes, contents and scope processes stipulated for the realization of certain training objectives. It requires students to possess knowledge and skills, and at the same time, it also embodies good ideological qualities and behavioral habits. Therefore, the essence of the curriculum is not only at the horizontal level of content, but also reflects the vertical process. The exploration of the order and rationality of the organization of the teaching content and its efficiency is a must for the educational organizers. Higher art and design education curriculum in the purpose and planning, in addition to the above common characteristics of the curriculum of colleges and universities, but also its individual characteristics. Its mission is to make the basic knowledge and professional skills in parallel, to cultivate comprehensive design talents to meet the needs of the market. The starting point of education should be based on the students to enter the society, the talents into the market, in the post can be organized, creative use of their basic knowledge, play its practical skills to practice activities. In recent years, the data on the change of supply and demand and the change of job satisfaction have shown many shortcomings in the training of human resources, so it is necessary to re-examine the old ways of setting up the curriculum that have been customized. In the context of today's main theme of social harmony, the art and design discipline, which combines technology and art, is facing a vigorous challenge. Opportunity is in front of us, we must quickly recognize the special characteristics of the art and design profession itself: the proportion of skill practice courses is large. The professional knowledge that guides the practice is rapidly updated. This requires more attention to the initiative of the learning subject in the course structure, clarifying the employment-oriented learning intention of the subject, and grasping the "variable" of professional knowledge - the trend and the "constant" - the traditional inclusiveness. The construction of higher art and design education courses should seek support from the following three aspects.

2.1.2. Directions for Designing Online Art Teaching Programs:

1) The selected courses should be like a “set menu”, with a mix of main and side dishes. Systematically “staple food” and “appetizer soup” and “dessert” clear distinction, that is to say, basic and applied professional courses should be clearly divided into primary and secondary professional courses, the arrangement of the sequence to be fixed, strictly follow the order of intake of knowledge from broad to specialized. In other words, basic and applied specialized courses should be clearly divided into primary and secondary, and the sequence should be fixed, strictly following the order of knowledge intake from broad to specialized. On this basis, students can also have the autonomy to choose relevant auxiliary knowledge, and the exercise of this right can be realized in the form of elective courses. In this way, students' learning will not only remain at the level of passive acceptance, but also reflect the ability of independent learning.

2) Curriculum design should be oriented to employment needs. On the issue of elective course curriculum mentioned earlier, there is a common problem in the curriculum of many art and design colleges and universities today, that is, the curriculum is oriented to the ability and preference of teachers to open elective courses. If the initial emphasis on the concept of running the school is to focus on the students' adaptability to employment, then there is no reason to put the cart before the horse in the curriculum of elective courses. Teachers should be required to update their skills in accordance with market needs. The cart before the horse here is not between teachers and students, but between the purpose of teaching and the purpose of learning. In other words, the curriculum of elective courses is not simply a matter of adjusting the knowledge structure around students' learning preferences. It is more accurate to say that elective courses should be organized in accordance with the students' employment orientation. Courses should be designed to be, firstly, clearly practical and, secondly, applicable to the needs of the market.

3) Curriculum design should adhere to the characteristic concept of “integrating trends and traditions”. Taking the elective course curriculum as an example, it is easy to find in the syllabus guided by this concept that the proportion of folk handicrafts, traditional culture courses (such as tie-dye, batik, weaving, etc.) and modern application technology processing courses (such as commercial photography, outdoor advertising, web page design, etc.) is close to one to one. The large proportion of traditional crafts reflects the characteristics of the school, as well as a strong humanistic concern for the arts and the times.

2.2. Concepts Related to SAM Agile Iterative Modeling

SAM is called Continuous Approximation Development Model, which emphasizes on breaking the course into pieces to develop, get user feedback quickly from the beginning of the course design, and ultimately approach the best course design standards.SAM theory is different from IDDIE theory, which provides a brand new course development model. In the ADDIE model, high-quality courses need to strictly go through the established process to be developed, which takes a long time. Although the courses developed by ADDIE are more comprehensive, the developers seldom consider the learning needs and experience of the learners, so the courses developed by ADDIE are often faced with the problem of “those who know the development technology don't know the profession, and those who know the professional knowledge don't know the development technology” in the actual operation. Therefore, ADDIE development courses often face the problem of “those who know development technology do not know the profession, and those who know professional knowledge do not know development technology” in practice, and the quality of the courses is often not high. Along with this series of problems, on the basis of ADDIE also derived from a lot of models, the most widely used is the SAM agile iterative model.

2.3. Online Course Design and Development Based on SAM Agile Iterative Modeling

SAM Agile Iterative Model is a design and development procedure that takes initiators, stakeholders, and learners into consideration throughout the design and development process.For developing online courses, SAM Agile Iterative Model is not an optimal way to go, and its model is shown in Figure 1 [22]:

From the characteristics of the model, SAM is belongs to the multiple cycle iteration model, in SAM model, the error occurs later or the expected goal is not reached, can be directly returned to the previous step of the design stage to re iterate the test.SAM agile iteration model is divided into 3 phases and 8 steps with 7 different tasks.

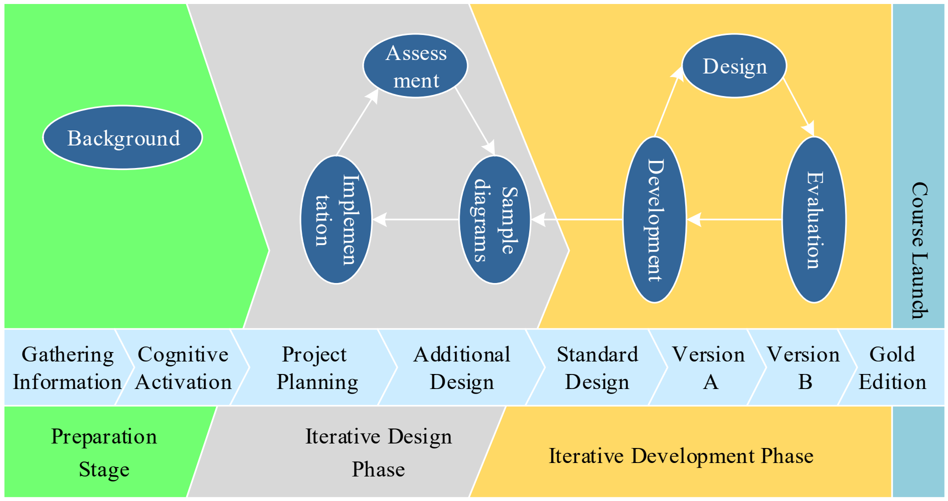

Fig. 1. SAM Agile curriculum development model

2.3.1. Preparation phase. The main task in the preparation phase is to gather background information before attempting to design the first option. The background information helps us to set goals, identify particular problems, and rule out other options. This phase prepares for the next phase of focused design activities by narrowing the focus.

1) Gathering Information. The preparation phase begins with gathering project background information that will be used to guide the design and communicate the resolution. Background information to be collected includes: previous performance improvement measures and results obtained, current application plans, available content materials, and organizational responsibilities for training. Constraints such as timelines, budgets, legal requirements, who is the final decision maker, and how to define project success. Information gathering should begin with the project leader by identifying the existing constraints (budget, schedule, or other factors) for the project. This information can help us determine how much effort should be expended during or after the kickoff meeting.

2) Cognitive Launch. Cognitive initiation contains a lot of vital purposeful information and it plays a key role in the completion of the activity. The Cognitive Launch process brings the key players together to avoid having to deliver information and reach agreements individually, makes it necessary for the designer to consider who is in charge and has the most influence, as well as who is the most difficult to please, and it clarifies the key measures for success.

2.3.2. Iterative design phase. This phase corresponds to the iterative phase of the general software development process, where development goals are accomplished incrementally through continuous iteration. But here we have a very significant difference: in the dual-iteration model, the requirements and testing team and the development team each perform their own independent iterations, and the two iteration cycles do not need to be strictly synchronized. That is to say, in many cases, the development team does not need to wait for the requirements and testing team to complete the current iteration cycle to enter the next iteration cycle, and vice versa.

1) Obtain a new milestone version of the development goal from the development team (or wait if it doesn't exist).

2) Evaluate whether the latest milestone version contains changes that are significant enough for end users. This assessment should include both the subjective judgment of team members (especially representatives of the software's end-users) and objective data criteria, such as

performing the latest End-to-End product tests on the new release, observing how well the tests pass, and so on.

3) If the assessment is that the current version does not contain sufficiently significant changes, the current iteration cycle ends and the next iteration cycle is entered.

4) If the evaluation result is that the current version contains significant enough changes, deliver this new phase version to end users for trial and collect their feedback. On this basis, start communication with users, continuously deepen and revise the knowledge and understanding of user needs, and respond to changes in user needs in a timely manner.

5) On the basis of the above work, amend and refine the End-to-End product testing for end users, reflecting the way the software is actually used (can be manual testing). The requirements and testing team needs to ensure that these tests are as comprehensive and detailed as possible, and can fully cover the requirements and testing team's current understanding and knowledge of user requirements. In particular, as the team identifies changes in user requirements, the collection of End-to-End tests needs to be modified accordingly. Finally, to the extent possible, the requirements and testing team should try to automate these End-to-End tests.

6) Perform new End-to-End product tests on the current version, identify the tests that the current version cannot pass, and provide feedback to the development team on these failed test cases and the associated understanding of user requirements. Accordingly, an iteration cycle for the development team consists of the following specific steps.

(1) Summarize the changes in understanding of user requirements since the previous cycle. This is based on the End-to-End product tests provided by the requirements and testing teams, and the feedback they provide after running the tests. At the same time, the conclusions from this step need to be communicated and confirmed with the Requirements and Testing team.

(2) Based on the requirements obtained in the previous step, determine the goals of the next phased release and design the software. In particular, "pass current End-to-End product testing" must be considered as a major goal in this step.

(3) Based on the design obtained in the previous step, the actual coding and implementation is carried out. It is important to note that unit testing is considered as part of coding and implementation and is the responsibility of the development team in this step.

(4) Delivery of a new stage version of the product that can pass End-to-End product testing at the design step.

2.3.3. Delivery phase. After the end of the dual iteration phase, the software process enters the delivery phase. At this point, the development team is no longer iterating, is no longer allowed to introduce new features, and is limited to fixing known defects. The requirements and testing teams are responsible for periodically running tests to ensure that the development team has not introduced new defects that cause the software to no longer meet specific user needs. When the defect rate drops to an acceptable percentage, the final software product is released and the software development process ends.

3. Evaluation of the learning effect of art courses based on the answers to online exercises

3.1. *Online Art Exercise Answers and Learning Effectiveness*

3.1.1. Online art instruction. The traditional model of education manifests itself in the form of teachers and students giving and listening to lectures in classrooms provided by schools. With the advancement of technology, online education was spawned. Prior to the New Crown outbreak, it was used more as a supplement to classroom learning, with few cases of online education in the large-scale regular school system. After the outbreak of the new crown epidemic, in order not to let education stagnate, large-scale regular teaching needs to be transplanted in online education as soon as possible, online education from the auxiliary to become the protagonist.

3.1.2. Assessment of learning outcomes. Knowledge tracking is a common tool for student online learning analysis, which is tasked with automatically tracking the process of changes in students' knowledge levels over time on their historical learning trajectories, and is used to predict how students will perform in future learning [23]. The more popular knowledge tracking models are (1) Bayesian Knowledge Tracking (BKT), (2) Deep Knowledge Tracking (DKT).

3.2. Modeling

In the dynamic key-value memory network, the “reading vector” represents the students' mastery of the current exercises, but it does not take into account the “forgetting” phenomenon that occurs in the learning process of the students themselves. Therefore, a model combining the forgetting curve and the dynamic key-value memory network is proposed.

3.2.1. Forgetting Curve. The forgetting curve is proposed by Ebbinghaus to describe the relationship between memory and time [24]. In general, the speed of forgetting is from fast to slow, the law of forgetting can effectively respond to the amount of knowledge remembered by students in the learning process (i.e., the degree of mastery of knowledge), with the passage of time, students will produce a process of forgetting, i.e., after students learn new knowledge, with the passage of time, if the students do not consolidate the knowledge repeatedly, then they will forget the knowledge in accordance with a certain law. Therefore, how to combine the law of forgetting with the knowledge tracking model is of great research significance. Usually, the mathematical form of the forgetting curve is a nonlinear function of the degree of memory retention (Rem) about the lag (t) between learning and testing. There are various forms of forgetting curves, and the most commonly used method for fitting forgetting curves is the power function, because the power function has a greater potential to contain the most ecologically valid quantitative description of the forgetting law compared to other functions over a sufficiently long time frame. The forgetting curves used in this paper are fitted power function models as shown in equation (1):

$$\mathrm{Re}\,m(t) = 0.19 + (1-0.19)\times 0.78\times(1+T)^{-0.68} \tag{1}$$

where $\mathrm{Re}\,m(t)$ denotes the amount of knowledge memorized with time lag t.

3.2.2. Dynamic Key-Value Memory Network (DKVMN) Modeling. The static matrix that stores the knowledge concepts is called the “key” matrix, and the dynamic matrix that stores and updates the level of mastery of the corresponding concepts is called the “value” matrix. The model involves two processes: the “reading process”, which is used to obtain the students' mastery of the exercises and to predict the probability of answering the exercises correctly, and the “writing process”, which is used to update the value matrix. The “writing process” is to update the value matrix. When the timestamp is t, let q_t denote the question number of the exercise the student worked on and y_t denote whether or not the student answered the exercise correctly, and use them as inputs to the model to obtain the predicted probability that the student answered the exercise correctly p_t, where y_t is a 0-1 variable, where 0 means that the student answered the question incorrectly and 1 means that the student answered the question correctly.

3.2.3. Dynamic Key-Value Memory Network (DKVMN-FGC) Model Based on Forgetting Curve. In Dynamic Key-Value Memory Network (DKVMN), the reading vector r obtained from the “reading process” represents the students' mastery level of the current exercises, but the forgetting law of students' learning is not considered here, so this paper proposes to combine the forgetting curve with the “reading process” to obtain the Dynamic Key-Value Memory Network model (DKVMN-FGC) based on the forgetting curve. Therefore, this paper proposes to combine the forgetting curve with the "reading process" to obtain the dynamic key-value memory network model (DKVMN-FGC) based on the forgetting curve. For a simple example, when the time point is t, the information of student 1 is input into the model, L_1 represents the total number of exercises completed by student 1, q_1 is the question number of the exercise sequence done by student 1 (in order of doing the problems), y_1 is the corresponding answer of student 1 to the exercise sequence q_1 (i.e., whether student 1 gives the correct answer to the exercise), so that the predicted probability p_t can be obtained, and p_t represents the predicted probability that student 1 answered the exercise correctly.

1) Symbolic labeling. Here, let the set of students be $x=\{x_1,x_2,\cdots,x_s\}$, the set of questions that student i is working on be $q_i=\{q_{1,i},q_{2,t}\cdots,q_{t,i}\cdots\}$, and the corresponding student exercise responses be $y_i=\{y_{1,i},y_{2,i},\cdots,y_{t,i},\cdots\}$. The input to the model is of the form:

$$\begin{cases} L_i \\ q_i=\{q_{1,i},q_{2,i},\cdots,q_{t,i},\cdots\} \\ y_i=\{y_{1,i},y_{2,i},\cdots,y_{t,i}\cdots\} \end{cases} \tag{2}$$

where L_i denotes the total count of exercises completed by student i (including repeated completions), where each element of y_i is a 0-1 variable, with 0 indicating that the student answered incorrectly and 1 indicating that the student answered correctly. The exercise label q_t is first multiplied with the exercise embedding matrix $A\in R^{Q\times d_k}$ to obtain the embedding vector k_t of the exercises, i.e., Equation (3). where A contains the features of all exercises and k_t contains the features of a single exercise.

$$k_t \leftarrow q_t \times A \tag{3}$$

Q represents the total number of different exercises, while d_k represents the dimension of the exercise embedding matrix (this value is set by human).

In the subsequent "read process" and "write process", there is a weight vector w_t, which represents the degree of relevance of the exercise and the underlying concept. In the "read process", w_t is used as the weight of the value matrix, and in the case of the "write process", w_t is used as the weight of the "clear vector". Therefore, the invalid content can be discarded to update the value matrix. And the correlation weight w_t is obtained by inner product of embedding vector k_t with key matrix M^k and using softmax as activation function, i.e., Equation (4):

$$w_t(i)=soft\max\left(\vec{k}_t^T M^k(i)\right) \tag{4}$$

2) Reading process. It is well known that the phenomenon of forgetting in the learning process is inevitable. However, the original dynamic key-value memory network model does not take this phenomenon into account, which may not be able to accurately assess the students' knowledge level. Therefore, a forgetting curve is added to the "reading process" to simulate the students' forgetting process.

The original dynamic key-value memory network used the read vector r_t to summarize the students' mastery of the current exercise. However, after adding the forgetting pattern, the reading vector changes, so g_t is used to represent the students' mastery of the current exercise after following the forgetting pattern. It is represented by equation (5) and equation (6):

$$r_t = \sum_{i=1}^{N} w_t(i) M_t^v(i) \tag{5}$$

$$g_t(i) = r_t(i) \times \mathrm{Re}\,m(t)(i) \tag{6}$$

where N indicates the number of potential concepts in the exercise.

Since the law of forgetting suggests that the closer to the current time t, the more knowledge is remembered and vice versa, the less knowledge is remembered. The inputs are arranged in chronological order, and here the dimension of the exercise embedding matrix is d_k, so the total number of lags for each input q_t is d_k. Figure 2 shows the amount of memory for successive exercises performed at moment t. The student remembers 100% of the knowledge at the current time t, with a lag of 1 for t_k and 2 for t_{k-1}, so the amount of knowledge remembered at t_k will be less than at the current time t, but more than at moment t_{k-1}, and the closer it gets to t_1, the less it will be remembered, and so on. Therefore, the time lag is set to $t = (d_k, d_{k-1}, \cdots, 1)$. Then, it is necessary to multiply the initial read vector r_t with the elements in the same position as the $\mathrm{Re}\,m(t)$ computed by Eq. (1) to obtain g_t.

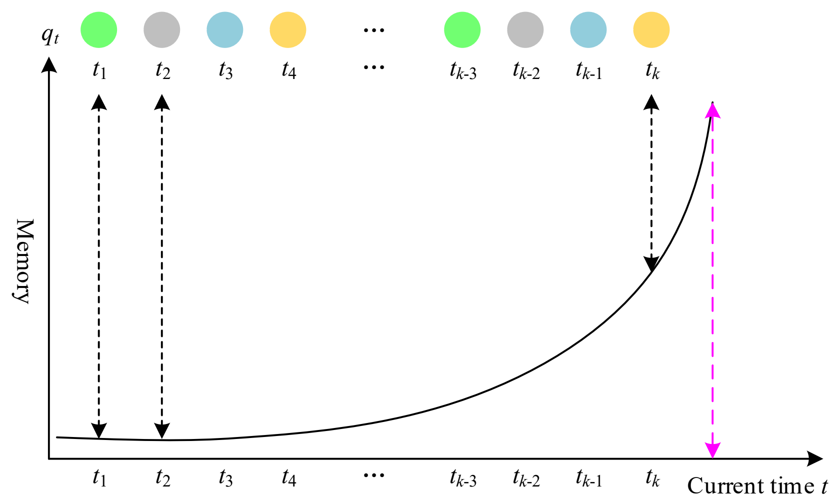

Fig. 2. The number of consecutive exercises performed at time t

As in the original Dynamic Key-Value Memory Network (DKVMN), the obtained read vector g_t based on the forgetting law is spliced with the embedding vector k_t, and then f_t is obtained through a fully connected layer with an activation function of Tanh, i.e., Eq. (7), whereas f_t contains the level of mastery of the student and the difficulty of the previously completed exercises:

$$f_t = \mathrm{Tanh}\left(W_1^T\left[g_t, k_t\right] + b_1\right) \tag{7}$$

Finally passing f_t through a layer of fully connected layers with a sigmoid activation function yields the predicted student mastery of the exercise p_t, i.e., the probability that the student will answer question q_t correctly, which in turn reflects the student's current learning effectiveness as shown in Equation (8) [25]:

$$p_t = sigmoid\left(W_2^T f_t + b_2\right) \tag{8}$$

3) Writing process. Finally passing f_t through a layer of fully connected layers with sigmoid activation function yields the predicted student mastery of the exercise p_t, i.e., the probability that the student will answer question q_t correctly, which in turn reflects the student's current learning effectiveness as shown in Equation (9):

$$p_t = sigmoid\left(W_2^T f_t + b_2\right) \tag{9}$$

The main purpose of the “write process” is to update the value matrix. Tuple $\left(q_t, y_t\right)$ represents the exercise question number and student responses, similar to the previous “read process”, and tuple $\left(q_t, y_t\right)$ is multiplied with its entry matrix $B \in R^{2Q\times d_v}$ to obtain the corresponding embedding vector v_t, where B contains the features of all tuples and v_t contains the features of individual tuples:

$$v_t \leftarrow \left(q_t, y_t\right) \times B \tag{10}$$

Next, the value matrix needs to be updated, which requires further computation of the “clear vector” e_t and “add vector” a_t, i.e., Eqs. (11) and (12). The “purge vector” is used to discard the invalid contents of the value matrix, while the “add vector” is used to add new contents to the value matrix. This refers to the fact that the value matrix needs to discard information about exercises that have been in the past for a long period of time, because the longer the interval between completed exercises in the past, the less representative they are with respect to the current time. At the same time, new exercise information needs to be added:

$$e_t = sigmoid\left(E^T v_t + b_e\right) \tag{11}$$

$$a_t = \mathrm{Tanh}\left(D^T v_t + b_a\right)^T \tag{12}$$

where E and D are the transformation matrices and their size is $d_v \times d_v$. Finally, the value matrix can be updated according to the “clear vector”, “add vector” and the value matrix of the previous moment, as shown in equation (13):

$$M_t^v(i) \leftarrow M_{t-1}^v(i)\left[1 - w_t(i)e_t\right] + a_t \tag{13}$$

where 1 denotes a vector with all elements 1, M_t^v is the updated value matrix at moment t, M_{t-1}^v is the value matrix before the update, and the weights of e_t use the same correlation weights $\vec{w}_t$ as before.

3.3. *Analysis of experimental results*

3.3.1. Experimental procedure. The purpose of this experiment is to compare the college users' memorization of art knowledge before and after using the online art teaching course designed in this study. 50 college students from the College of Fine Arts, University of H were selected to conduct a 60-day experiment divided into two phases: the first phase of the first 30 days, on the first day of the experiment, the respondents memorized the art knowledge points in accordance with their own customary way method, and on the 30th day, they will be Examined to find out the number of art knowledge points that the respondents can write on the 30th day.

1) Pre-test. The results of 50 students in the first stage of the study are the data of the control group, they memorize 60 knowledge points according to their own customary method of memorizing art knowledge points, during which they can review or not according to their own plan, according to the survey, these methods are widely used in the college student group. During the learning process, the

respondents need to record the memorized art knowledge points, and after the first stage, each respondent was tested to get the results of the experimental pre-test.

2) Post-experimental test. The learning results of 50 respondents in the second stage are the data of the experimental group, who use the art online course system designed in this research will remind the respondents to review these knowledge points on the 2nd, 4th, 8th, 15th, and 30th days after learning. The biggest difference with the first stage is that the system will remind the user to review the operation of what they have learned according to the Ebbinghaus forgetting curve in a timely manner in order to memorize the words more firmly. At the end of the second phase the results of the experimental post-test were derived and recorded by means of a test.

3.3.2. Increase in total memory. In order to use the comparison of the results obtained before and after this study more intuitively, the paired samples t-test in SPSS software was used to compare the data of the experimental pre and post-tests, and the following are the results of the compared data, and Fig. 3 shows the experimental pre and post-tests paired samples t-test.

As can be seen in Figure 3, the mean value of the respondents' art knowledge memorization ability in the experimental pre-test is 35.259, and the mean value of the post-test is 53.1254, and it is obvious that, from the mean value, there is a significant improvement in the performance of the respondents after using the online art teaching course system designed in this study. The data comparison between the respondents' test results in the pre-experiment and the post-experiment showed that the Sig value of the paired test was 0.000, 0.000<0.05, which indicated that the difference between the results of the pre- and post- side of the experiment was significant, and that the mean score of the post-experiment was improved by 17.8664 points nearly 18 points compared to the pre-experiment. It is obvious that the effect of using the online course of art learning based on Ebbinghaus forgetting curve is more significant on the learning of art knowledge than other applications.

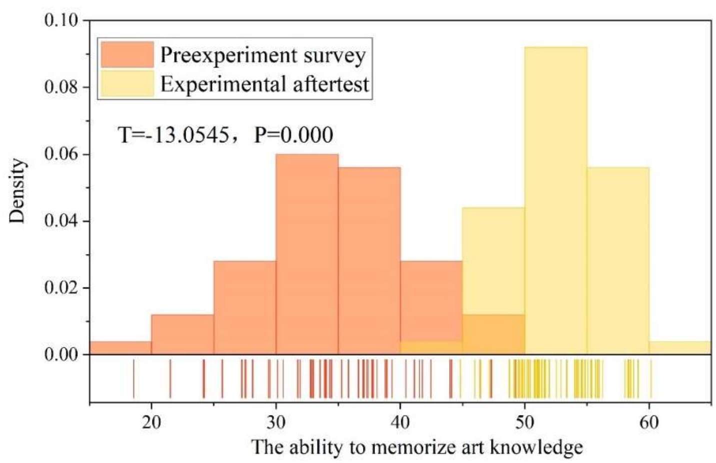

Fig. 3. Test and post-test pair sample t test

3.3.3. Interest in Art Learning in Online Courses Based on the Forgetting Curve. Interest is the best teacher of students' learning, and it is the inner driving force of students' learning, which can make students continuously take the initiative to draw knowledge, thus pushing them to show enthusiasm in their behavior and improving their self-consciousness. If students' interest in learning is well stimulated, it can reduce teachers' supervision and parents' urging. Therefore, this study designed four questions on this dimension to investigate the effect of students' use of online art teaching courses on their learning interest, and the results are shown in Figure 4. A-D in the figure represent that using the online course of art learning with the forgetting curve can promote the communication between teachers and students, preferring the learning mode of the online art teaching course based on the forgetting curve to the traditional teaching mode, being more interested in learning by using the online art teaching course, and being willing to share the online course of art learning with the forgetting curve to other learners.

97.36% of the students indicated that they preferred the teaching mode under the application of the online art learning course based on the forgetting curve to the traditional art teaching mode, because in the experiment, students were able to personalize the remediation of cognitive deficiencies, and there was a scientific remedial learning method to guide students to remediate the knowledge successfully, and the guidance of the method made students feel confident in their learning, stimulated their learning interest, and intrinsically driven to learn knowledge, so 94.98% of the students are willing to share the online course of art learning of this forgetting curve to other learners, which shows that most of the students are satisfied with the experiment of the online course of art learning of this forgetting curve. Based on the above statistical analysis of the questionnaire data, it can be concluded that the online art teaching course based on the forgetting curve can be applied in actual teaching and the application effect is good.

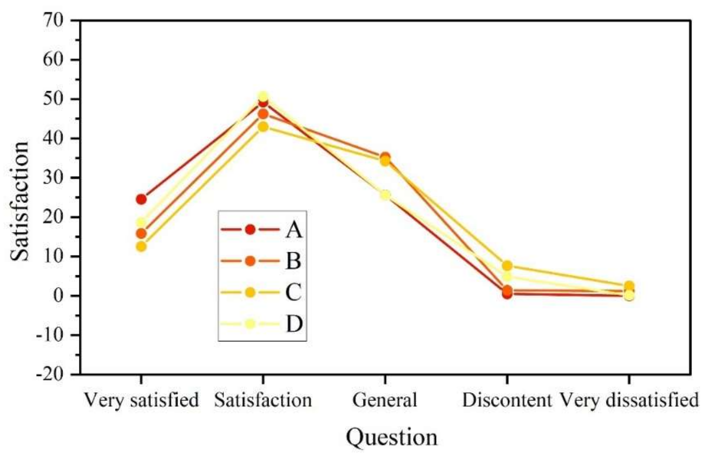

Fig. 4. The effect of forgetting curve on student interest based on forgetting curve

4. Evaluation of online art teaching course design and analysis of its impact on instructional delivery

4.1. Appraisal and feedback evaluation process based on big data

4.1.1. Effectiveness of teaching online art courses. SPSS20 statistical software was used to statistically analyze the scale indicators, and the statistical results from the questionnaire were analyzed as shown in Figure 5, where A-F are the degree to which the online course promotes independent learning, the degree to which the online course improves the ability to communicate and express themselves, the degree to which the online classroom improves professional knowledge, the degree to which the online classroom improves the ability to ask questions, and the degree to which the online classroom improves the ability to think about problems, Degree to which the online classroom improves problem-solving ability students' adaptation to the online course, the subject students' understanding of the teaching content of the online course are high, and they have a high degree of interest in the course, which meets the expected goals. Students' ability to communicate and express themselves (5.7618), to ask questions (5.6413) and to solve problems (5.6426) has been significantly improved through this course.

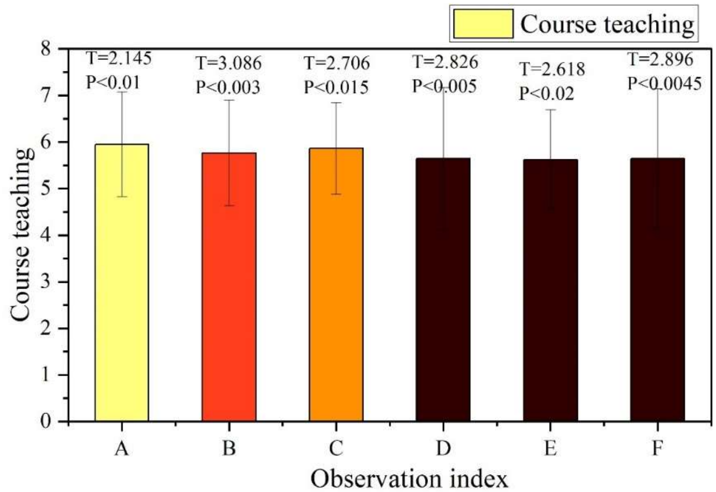

Fig. 5. The results of the course teaching effect

4.1.2. Comparison of results. Figure 6 shows our school's and overall excellence rates and average grades for 2019-2021, which are the statistics of excellence rates and average grades for the three years (2019-2021) of the online fine arts teaching program. From Figure 6, it can be seen that (1) almost all of the data in the last three years exceeded the overall data, which indicates that the quality of teaching at the subject school is higher than the average quality of all colleges and universities that take this online course. Our school excellence rates for 2019 and 2020 are 78.168% and 54.963%, respectively. The overall excellence rates for 2019 and 2020 are 59.569% and 47.169%, respectively. (2) The excellence rates and grade point averages for the spring and summer semesters of 2019 were higher due to the fact that this was the time when art courses were taught in a predominantly online format, and faculty and students were able to communicate face-to-face with each other on a regular basis about teaching and learning issues. (3) The excellence rate and grade point average for the spring/summer 2020 semester decreased because teaching was forced to go offline this semester, and students and faculty generally felt uncomfortable and ill-prepared for teaching, and there were miscommunications in teaching and its tutoring. (4) In the spring and summer semesters of 2021, this is when the excellence rate and grade point average rebounded as faculty and students became accustomed to the online course format and technical issues and performance of the online platform improved. Our excellence rate and grade point average were 50.565% and 85.695, respectively. (5) The overall data curve of the past three years shows a “V” shape, but the data shows a continuous decline, which needs to cause the teaching team to think deeply and make timely adjustments. (6) Compared with online courses, the excellence rate and average grade of online courses are higher, which is in line with the general phenomenon.

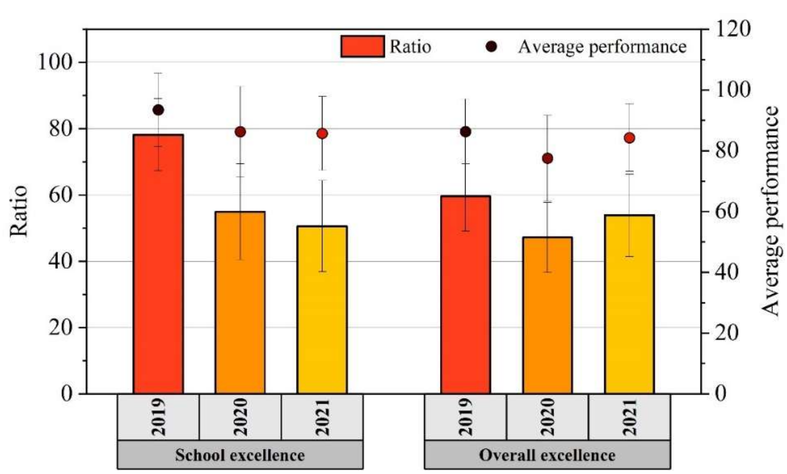

Fig. 6. 2019-2021 and the overall excellence of the school and the overall excellence rate

4.1.3. Satisfaction. The number of valid questionnaires in 2019-2021 at University H is 50, and the overall number of valid questionnaires is 5000. And combined with the questionnaire question of the online art teaching course, "Comprehensive evaluation: do you think the art course is general and inspiring, and the course is more rewarding?" In the spring and summer semester of 2019-2021, the data were calculated as shown in Table 1, and in the spring and summer semester of 2019, the score of College H was 91.826, and the overall score was 90.625.

Table 1. 2019-2021 spring and summer semester data calculation

Run semester		School			
		Very satisfied	Satisfaction	General satisfaction	Discontent
Spring and summer in 2019	Vote (person)	32	12	4	2
	Turnout (%)	0.64	0.24	0.08	0.04
	Score (score)	91.826			
Spring and summer in 2020	Vote (person)	30	13	5	2
	Turnout (%)	0.6	0.26	0.1	0.04
	Score (score)	89.26			
Spring and summer in 2021	Vote (person)	31	14	4	1
	Turnout (%)	0.62	0.28	0.08	0.02
	Score (score)	90.065			
Run semester		Population			
		Very satisfied	Satisfaction	General satisfaction	Discontent
Spring and summer in 2019	Vote (person)	3003	1621	320	56
	Turnout (%)	0.6006	0.3242	0.064	0.0112
	Score (score)	90.625			
Spring and summer in 2020	Vote (person)	2865	1799	300	36
	Turnout (%)	0.573	0.3598	0.06	0.0072
	Score (score)	90.563			
Spring and summer in 2021	Vote (person)	2936	1839	200	25
	Turnout (%)	0.5872	0.3678	0.04	0.005
	Score (score)	91.755			

4.1.4. Increased student achievement. Figure 7 shows the histogram of students' art achievement improvement, this data set collected data information of 5000 students, the average enrollment grade and improved average grade of each level, administrative class and teaching class are different, in order to unify and comprehensively analyze the change of students' art achievement after enrollment, the average of the difference of two semesters of test scores relative to enrollment grades (referred to as pcstg) will be taken as the average of the difference of two semesters of test scores relative to enrollment grades as the dependent variable of this model's dependent variable, open SPSS's analysis-descriptive statistics-exploration, and use pcstg as a list of dependent variables to get the histogram: as seen from the data in the figure, the overall test scores have improved by an average of 24.14704, with a standard deviation of 23.6518 and a normal distribution, thus indicating that throughout the whole process of teaching and learning, most of the students' scores have improved.

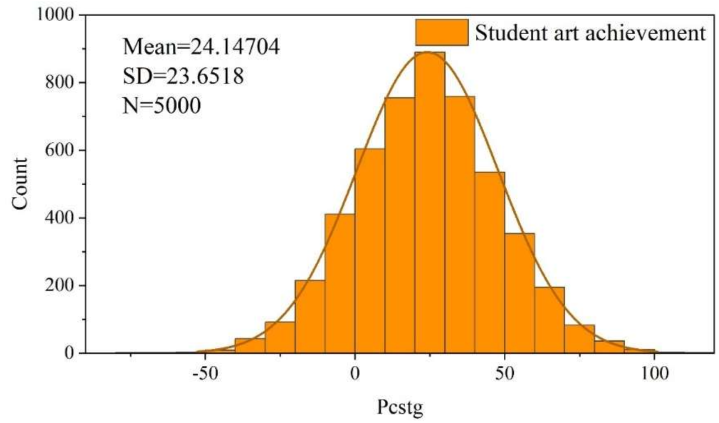

Fig. 7. The student's artistic achievement improved the histogram

4.2. *Impact of big data aids on instructional delivery*

Table 2 shows the analysis of the impact of big data aids on instructional delivery, where X1-X4 represent the teacher's use of big data aids, use of heuristics, use of inquiry, and incorporation of hands-on instruction.

The full sample model regression results show that overall the teacher's use of big data aids for online art instruction significantly affects instructional delivery, t=1.245, P=0<0.05, which is significantly positive at the 1% level. And the more adequate the use of technological tools (i.e., the more adequate the incorporation of new technological tools for instructional design or organization of instruction), the higher the probability that students will rate their teachers' satisfaction with instructional delivery. Meanwhile, both the full-sample regression results and the regression results of each subgroup sample showed that teachers' teaching effectiveness was significantly influenced by teaching methods such as heuristic, inquiry, and hands-on teaching methods, and the more adequate the use of these teaching methods, the higher the probability that students rated their satisfaction with the effectiveness of teaching delivery.

Table 2. Large Numbers are aided by the impact analysis of teaching delivery

Variable	Full sample	Q1		Q2		Q3	
		High intelligence group	Medium group	Boys' group	Group of girls	Senior group	Low grade
Constant term	1.245***	1.436***	1.241***	1.188***	1.218***	1.185***	1.247***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
X1	-0.089***	-0.024	-0.125***	-0.034	-0.164***	-0.174***	-0.059
	(0.005)	(0.971)	(0.003)	(0.548)	(0.003)	(0.003)	(0.174)
X2	-0.158***	-0.272***	-0.157***	-0.148**	-0.214***	-0.182**	-0.196***
	(0.00)	(0.002)	(0.003)	(0.041)	(0.000)	(0.016)	(0.000)
X3	-0.186***	-0.225**	-0.174***	-0.215***	-0.157***	-0.175**	-0.184***
	(0.000)	(0.015)	(0.002)	(0.025)	(0.026)	(0.026)	(0.000)
X4	-0.351***	-0.421***	-0.348***	-0.248***	-0.214***	-0.415***	-0.248***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Chi2	492.25***	186.254***	218.664***	182.666***	218.55***	181.699***	245.597***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Log likelihood	-980.364	-214.654	-648.691	-251.648	-648.695	-218.694	-574.869
N	5000	2615	2385	2536	2464	1866	3134

5. Conclusion

In this paper, we sort out the direction of online art course design, start from the preparation stage, iterative design stage, and delivery stage, and use the SAM agile iterative model to design and develop online art teaching courses. Combined with the forgetting curve model, the effectiveness of online art teaching is evaluated, and at the same time, the impact of big data-assisted technology on teaching delivery is analyzed. Respondents' ability to memorize art knowledge was 35.259 points in the experimental pre-test, and the mean value of the post-test was 53.1254 points, and after the paired test, the Sig value was 0<0.05, and the mean score of the post-test was 17.8664 points higher than that of the pre-test. The scores of students' communication and expression ability, problem posing and problem solving ability were 5.7618, 5.6413 and 5.6426 respectively through the online art course, and the P-values were all <0.05, and the students' art learning ability was significantly improved. Comparing the online art course scores for the three years from 2019-2021, the excellence rate of our school was 78.168% and 54.963% in 2019 and 2020, respectively.The overall excellence rate was 59.569% and 47.169% in 2019 and 2020, respectively. Using regression analysis to analyze the impact of big data aids on instructional delivery, the overall use of big data aids by instructors for online art instruction significantly affects instructional delivery, t=1.245, P=0<0.05, significantly positive at the 1% level. It indicates that the more adequate the use of big data aids, the higher the probability of students' satisfaction ratings on the effectiveness of instructional delivery.

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