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The Teaching Mode Design and Effect Evaluation Method of Animation Course From the Perspective of Big Data

Zhongqiang Feng, Henan Vocational Institute of Arts, China
Yi Zhang, Zhengzhou University, China*

ABSTRACT

OBE concept is a new teaching mode which emphasizes the improvement of students' subjective initiative and professional practice ability. The teaching of animation course is based on drawing and computer, which requires teachers to understand the OBE mode of animation course, carry out targeted teaching innovation of animation course, and adjust the traditional teaching methods, teaching contents and teaching assessment methods. Based on the MOOC platform from the perspective of big data, this paper analyzes the teaching status and innovation process of animation course, and puts forward a hybrid animation course teaching method. Through the research of 686 primary and secondary school teachers, the results show that the hybrid animation course teaching based on OBE and MOOC from the perspective of big data has a better effect than the traditional teaching method, which improves students' initiative in learning animation courses and greatly enhances students' acceptability in learning animation courses.

KEYWORDS

Animation Course, Big Data, Effect Evaluation, OBE Model, Teaching Mode

2013 was the first year of development for China's massive online open course (MOOC) platform. In this year, some key universities, government departments, and enterprises in China invested in the construction of large-scale open online course platforms. However, throughout the country's major universities, fewer than 10% of these institutions can effectively build high-quality MOOC platforms. Chinese MOOC learners are mainly distributed in first-tier cities and cities with developed education. Many local universities still lack methods to promote the construction of curriculum content and the implementation and promotion of hybrid teaching reform methods. Especially for majors, such as animation, that require high practical abilities, traditional classroom teaching cannot meet the needs of students for knowledge, practical skills, and social talent development. Effective teaching method innovation is imperative. As a new teaching method, the research and exploration of the teaching

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*Corresponding Author

mode of animation courses in the context of MOOC is an important way to cultivate talents with both knowledge and ability, and a key means to cultivate excellent socialist successors. In practice, MOOC and traditional teaching modes are usually combined with each other. This combination can, on the one hand, provide higher quality teaching resources and more diverse teaching formats for the cultivation of talents in universities. On the other hand, it has far-reaching implications for the promotion of curriculum reform and innovation of education models.

The change in teaching of animation courses should be based on the needs of enterprises and society. At present, universities have recognized the importance of cultivating students' practical skills and are committed to making innovations in teaching. Particularly in practice-based professions, schools are pursuing effective school-enterprise cooperation. There is also a need to re-plan the curriculum system, which should also be reconstructed in terms of teaching needs and the current state of teaching development. In terms of assessment of learning outcomes, students' learning outcomes are used as a guide to form a new learning process. For the animation course, the design process requires the mastery of competencies including the application of design software, but also basic sketching skills. In learning, teachers are committed to developing comprehensive competencies. Once the teaching objectives are clearly defined, students are divided into groups and a project-based teaching approach is implemented to develop their interest.

Outcome-based education(OBE) is a new teaching model that focuses on students and on learning outcomes. In this teaching and learning mode, students can experience a series of practical operations and applications in the course, thereby improving their professional skills and creativity. Under the OBE model, traditional teaching models should be innovated to achieve efficient teaching and learning. First, a teacher-based teaching model can be transformed into a student-based learning model, such as teaching guidance and rearrangement of teaching content. Secondly, student assessment focuses on assessing students' skills in achieving learning outcomes. The development of student learning concepts is usually accompanied by the development of professional and general literacy. This requires a student-centered approach that values the experiences students have in achieving outcomes and the skills they acquire in the process, resulting in a teaching model that is more appropriate to the development of teaching and learning in higher education in the new era.

Faced with the current problems of teachers' low level of teaching ability in animation courses, students' weak awareness of big data, insufficient teaching facilities' ability to obtain and apply educational data, low level of intelligent technology innovation and application ability, and insufficient attention paid to students' personalized learning needs, in this paper the authors analyze the teaching status and innovation process of animation courses based on the MOOC platform under the perspective of big data and propose a corresponding effect evaluation method. The authors' findings show that the teaching of OBE animation courses from the perspective of big data has better results than traditional teaching methods. The authors put forward targeted development suggestions, including improving the theoretical system of teachers' precise teaching ability, strengthening the interconnection and integration of big data in education, and building a service environment for precise animation course teaching. In this study, the authors explored the application of OBE and MOOC in animation course teaching from the perspective of big data, which is a relatively new research topic in this field. Secondly, the authors provided a comprehensive evaluation method to compare the effectiveness of traditional teaching methods with the proposed blended teaching methods. In addition, the authors provided practical suggestions to improve teaching quality and promote the development of personalized learning.

THEORETICAL BACKGROUND

The theoretical background of this study is mainly based on the following two aspects of theoretical support: OBE teaching mode and MOOC education platform.

OBE is a student-centered education and teaching model that emphasizes students' learning outcomes and practical abilities. The OBE teaching model emphasizes students' subjective initiative and achieves teaching objectives by evaluating learning outcomes. Compared to traditional teacher-based teaching models, the OBE teaching model places more emphasis on students' learning experience and outcomes. Under this model, students can operate and apply the knowledge they have learned in the course, thereby improving practical ability and creativity.

MOOC education platform is an educational and teaching platform based on Internet technology, with the main feature that students can use various course resources provided on the platform anytime and anywhere for learning. The MOOC education platform not only has extremely rich educational resources, but can also provide personalized learning services based on students' learning situations and needs. At the same time, it can analyze students' learning behavior through big data technology, ultimately achieving teaching objectives.

Drawing on the above two theoretical backgrounds, the authors explored the design and effectiveness evaluation method of animation course teaching mode based on the MOOC platform from the perspective of big data.

LITERATURE REVIEW

The development of Internet technology and the application of MOOC platforms have brought new opportunities and challenges for the education industry, especially for the teaching of practical courses such as animation. Animation education requires students to master both theoretical knowledge and practical skills, as well as to develop their creativity and innovation abilities. However, traditional teaching methods and assessment systems may not be able to meet the needs of animation education in the era of big data and online learning. Therefore, it is necessary to explore new teaching models and methods that can improve the quality and effectiveness of animation education.

One of the possible solutions is to adopt the OBE model, which is a student-centered and results-oriented approach to teaching and learning. OBE emphasizes the achievement of predefined learning outcomes that reflect the knowledge, skills, attitudes, and values that students need to acquire in a certain course or program. OBE also requires teachers to design appropriate learning activities, resources, feedback, and assessment methods that can facilitate students' learning process and measure their learning achievements. OBE has been widely applied in various fields of education, such as engineering, medicine, nursing, and business (Biggs & Tang, 2011). There is no single or best way to implement or evaluate OBE, but various authors have suggested some general principles and guidelines. For example, Spady (1994) proposed four levels of OBE implementation: Classroom reform, program alignment, external accountability, and system transformation. Harden (1999) suggested a four-step approach to OBE curriculum development: Outcome identification, outcome implementation, outcome assessment, and outcome evaluation.

Another possible solution is to integrate MOOC platforms into animation education. MOOCs are online courses that are open and free for anyone to enroll and learn. MOOCs provide learners with access to high-quality educational resources and interactive learning environments, as well as opportunities to collaborate and communicate with peers and instructors from different backgrounds and locations. MOOCs have been recognized as a powerful tool for promoting lifelong learning, democratizing education, enhancing employability, and fostering innovation (Yuan & Powell, 2013). Research in the field of animation education has shown that MOOC platforms can provide diverse, flexible, and personalized learning paths for animation learners to adapt to different learning goals, styles, and needs (Chen et al., 2019; Lee et al., 2020; Wang et al., 2021). The MOOC platform can also use various animation technologies and tools (e.g., 3D modeling, motion capture, and virtual reality) to enhance the creativity, expression, and communication ability of animation learners (Huang et al., 2018; Liu et al., 2019; Zhang et al., 2020). In addition, the MOOC platform can promote social interaction and knowledge sharing among animation learners to establish a dynamic and supportive learning community (Chen et al., 2017; Kim et al., 2014; Li et al., 2020).

However, there are also some challenges and limitations associated with OBE and MOOCs in animation education; for example, how to:

- Design and implement effective blended learning strategies that combine online and offline learning modes.
- Motivate and engage students in self-directed and collaborative learning.
- Provide timely and constructive feedback and support for students' learning progress.
- Assess students' learning outcomes in a valid, reliable and fair way.
- Ensure the quality assurance and accreditation of animation courses and programs.
- Deal with the issues of plagiarism, cheating, dropout and completion rates in MOOCs.

Therefore, in this study the authors aimed to explore the current situation and innovation process of animation education based on big data perspective under the MOOC platform, and to propose a hybrid teaching method that combines OBE with MOOCs for animation courses.

BLENDED LEARNING THEORY

After more than two decades of development, blended learning has been widely valued by countries around the world and is being used more and more widely in basic education and higher education (Porter et al., 2014). The Sloan Consortium defines blended learning as a combination of face-to-face and online teaching, combining two historically separate teaching models: Traditional face-to-face teaching and online learning (Porter et al., 2014). This conceptual definition of blended learning based on physical characteristics is widely accepted by academics.

According to Feng et al. (Pinto & Leite, 2020), the concept of blended learning can be analyzed in terms of two dimensions: Physical characteristics and pedagogical characteristics, and can be divided into technology application stage, technology integration stage, and big data stage (Table 1).

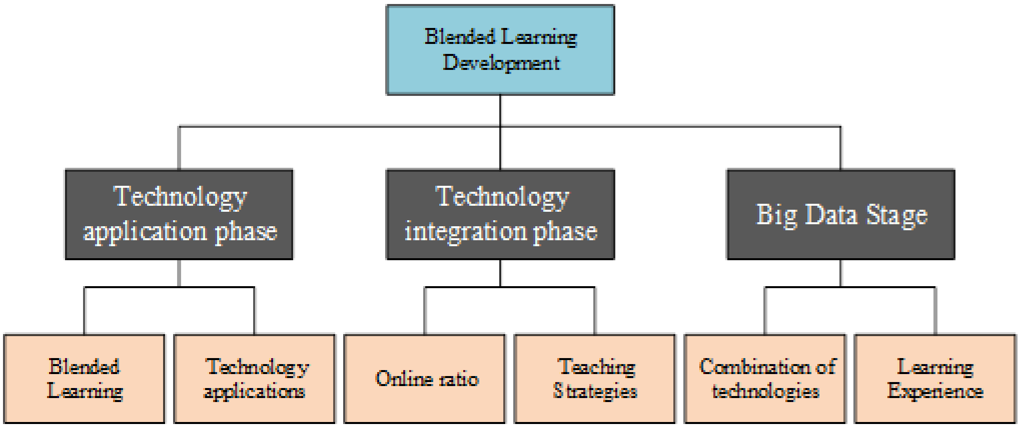
Figure 1 shows a structural diagram of the stages of blended learning development.

Blended learning and teaching are subject to constant change as technology evolves. The emphasis on the design of web-based online teaching models needs to be accompanied by an emphasis on the developmental transformation process of the learning experience. The focus is different at different stages. In scholars' understanding, blended learning and teaching is a process that has been influenced by technological developments and is constantly evolving. It has undergone a developmental shift from an emphasis on online learning content to an emphasis on the design of Web-based online teaching models, and then to an emphasis on the learning experience. The focus at different stages has been on technology, teachers, and students, respectively. Thus, some scholars have pointed out that blended learning with mobile Internet technology is not simply a mix of technologies, but a truly highly engaging and personalized learning experience for students (Zhang et al., 2022). Blended learning is not just a mix of face-to-face and online teaching; it is a mix of teaching and tutoring styles in a

Table 1. Classification of Blended Teaching Development Stages

Category	Technology application phase	Technology integration phase	Big data stage
Physical dimension	Blended learning	Online ratio	Combination of technologies
Pedagogical dimension	Technology applications	Teaching strategies	Learning experience

Figure 1. Structure of the Stages of Blended Learning Development



learning environment (Goodyear & Dudley, 2015). Thus, the evolution of the concept of blended learning is also a process in which the focus on physical characteristics diminishes and pedagogical characteristics increase.

Teacher Data Literacy

Data literacy is the consumption of knowledge and the ability to think about data in a continuous and cross-cutting way (Shen, 2015). In the era of big data, the center of animation training should shift from focusing on programming capabilities to focusing on programming and data processing. In the construction of animation courses, a data-centric curriculum system should be built to enable animation students to master the necessary knowledge and skills of big data, and have the basic ability to construct a big data framework, analyze, and process big data. Data literacy is an essential core literacy for teachers in the information age, and is the basis for teachers to make teaching decisions and carry out personalized teaching (Maybee &Zilinski, 2015). As such, according to the U.S. Department of Education's Education Sciences Research Center, data analysis and use are key to improve the quality of teaching and learning. Both the Educational Leader Standards and the Model Core Teaching Standards, on which existing U.S. teacher certification is based, include data literacy skills as a required assessment item (Mandinach, 2012). Further, the U.S. Department of Education's Office of Planning, Evaluation, and Policy Development suggests that teachers in the era of big data should have specific skills in five areas, including data orientation, data understanding, data interpretation, data-based instructional decision making, data-expanding questions, and new ideas for teaching and learning (Means et al., 2011). The U.S. government has also launched a series of innovative projects and programs focused on data literacy to promote the overall improvement of teachers' data knowledge and skills.

For teachers, improving data literacy is both one of the components of improving personal literacy and one of the main aspects of promoting data literacy education practices (Bejar, 2017). According to Professor Gurman of American Psychology, data literacy is the ability of teachers to understand and use data effectively and to make decisions and implement them accordingly. It consists of a set of specific skills and knowledge that help educators transform educational data into useful information and ultimately into actionable knowledge. This includes the ability to identify, collect, organize, analyze, summarize and process data, and to develop, plan, implement, and monitor action plans based on data (Dunlap & Piro, 2016). According to Mandinach (2012), teacher data literacy is the ability to integrate scientific data into real-life teaching and learning processes, where teachers are

Table 2. Comprehensive Comparison of Teaching Models and Related Concepts in Teacher Animation Courses

Category	Technical competence	Teaching skills	Data literacy
Competence objectives	Technical optimization	Quality improvement	Data processing
Competency requirements	Resource processing	Teaching integration	Data processing
Competency structure	Application innovation	Teaching ability	Data awareness
Competency characteristics	Teaching optimization	Subject technology	Data analysis

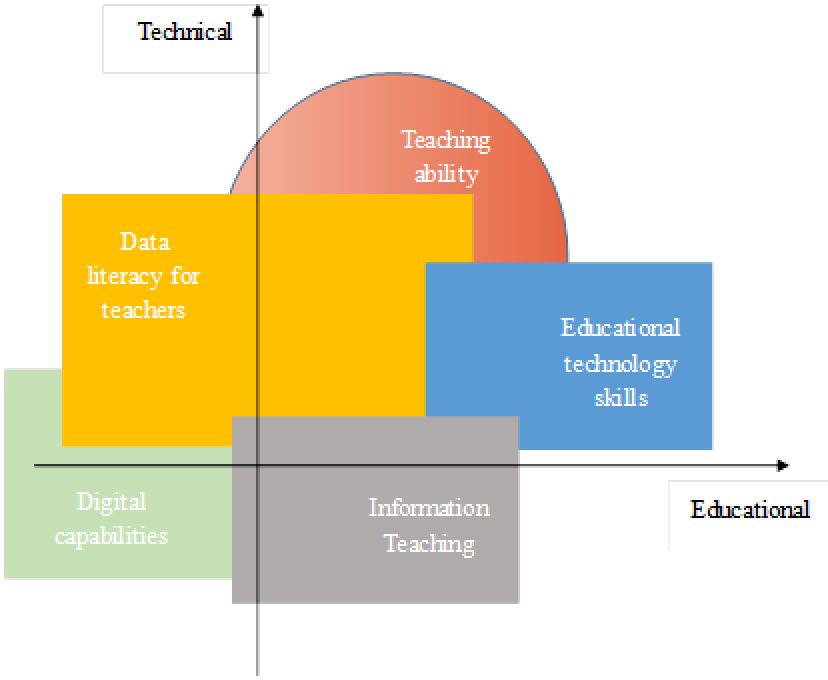
able to integrate subject-related knowledge, teaching activities, and expertise with educational data to achieve the goal of improving student learning.

Based on the data processing process, Chinese scholar Zhang Jingbo proposed that data literacy refers to teachers' ability to collect, organize and manage, process and analyze, share and collaborate, and innovate with data, as well as teachers' ethics and behavior in the production, management, and dissemination of data (Sun & Li,2022). Xiao-Han (Xiao-Han et al., 2021) discerned the definition of data literacy from the perspective of teachers' data wisdom. Jinliang and Baozhen (2015) explored the problems faced by teachers' data literacy and the development path from the concept and value of data literacy. Hao Yuanling et al. (as cited in Raffaghelli & Stewart, 2020) investigated the development of data literacy among university teachers in Shanghai from five aspects, namely, data attitudes, data awareness, data knowledge, data skills, and data services, and found that the data attitudes and awareness of university teachers were relatively positive, but data knowledge and skills were insufficient. Septiani & Rejekiningsih (Septiani & Rejekiningsih, 2020) considered teachers' data literacy as the ability of teachers to locate, acquire, process, and analyze different types and sources of educational data, and to translate the analysis results into knowledge for improving teaching behaviors in order to enhance their own professional skills and students' learning outcomes.

The competency requirements of teachers need to correspond to the competency objectives and reflect the main orientations of the competencies. The understanding of teachers' competencies related to educational technology is a process of integrating resources. In terms of competency composition and characteristics, various teacher education technology-related competencies identify psychological traits such as awareness and attitudes as key aspects that constitute competencies, as well as the pedagogical application and innovation of related technologies. As competencies are psychological characteristics that are expressed in specific activities, a discussion of teachers' competencies cannot be entirely divorced from individual psychological traits such as awareness and attitudes, and, in particular, individual awareness and attitudes need to be analyzed as key dimensions when discussing the composition of teachers' precise teaching competencies. Table 2 shows a comprehensive comparison of teacher competencies and related concepts for teaching in animation courses.

A comprehensive comparison of the above concepts of teacher education technology-related competencies reveals that teachers' information technology teaching competencies, education technology competencies, digital competencies, and data literacy, all of which emphasize the importance of technology to teachers' teaching, discuss the changes in teachers' competencies as a result of technology intervention and integration with technology from different perspectives. These abilities can help teachers better cope with the teaching changes brought about by technological intervention and integration, and continuously improve their teaching level and ability. At the same time, this shows that teachers need to constantly learn and adapt to the development of technology in order to better adapt to the needs of modern teaching. Figure 2 shows a comparison of the competency relationships of several technology competencies.

Figure 2. Comparison Chart of Teachers' Technical Skills

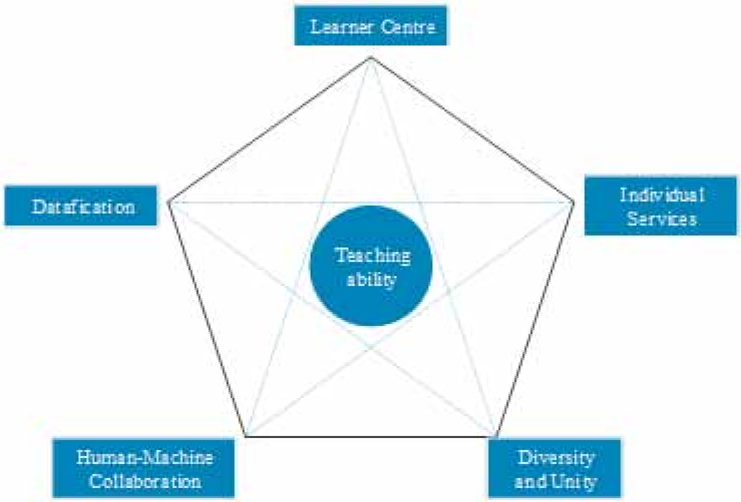


Characteristics of Teachers' Teaching Competencies in Animation Courses

A summary of the characteristics of teachers' teaching competencies in animation courses will allow to better understand the meaning of teachers' precision teaching competencies. Therefore, it is important that the summary of teacher competencies for animation courses takes into account the core features of the precision teaching model and is integrated with the characteristics of precision teaching. The authors emphasize the technical, data-based, intelligent, personalized, and accurate features of the teacher animation course teaching competence, while teaching usually emphasizes the educational, service-oriented, and leading features of the teacher animation course teaching competence. Figure 3 shows the summary and categorization of the characteristics of teacher animation course teaching competencies into five areas, with the specific information.

"Learner center" refers to the fact that teachers focus on exploring the subjectivity and creativity of students in the teaching process to meet their personalized and developmental needs. With the help of "datafication," teachers can learn about students' learning situations and problems in a timely manner through data-based means. Regarding "individual services," teachers should provide targeted teaching support and assistance based on students' different needs and learning differences, to help students better master animation production skills and methods. "Human-machine collaboration" emphasizes that teachers can provide better learning environments and resources for students through digital technology. "Diversity and unity" refer to the need for teachers to focus on various teaching forms and methods, such as classroom explanations, interactive discussions, practical operations, and case studies, to meet the different needs and learning methods of students, while maintaining consistency in teaching objectives.

Figure 3. Key Features of Teacher-Animated Course Instruction



TEACHING MODEL DESIGN COMPONENTS

After deep thinking, the authors initially identified the components of the teaching model design and their description. However, these elements were still at the initial stage and the relationships between them are not clear, yet. Therefore, the authors needed to use the experience of experts to refine the components of the teaching model and, in particular, to evaluate the scientific and rational nature of the components. Through the application of two rounds of Delphi method, the researchers made back-to-back anonymous consultations and corrections in order to obtain relatively sound and reasonable components of the teaching model design and to lay the foundation for the next step in the construction of the teaching model design. Because the Delphi method is usually based on the selection of leading experts in the relevant field, and multiple rounds of back-to-back, the authors used anonymous consultations. They used the Kendall coefficient to reflect the convergence of experts' opinions; in this process, experts need to be confidential and noncommunicative with each other.

Selection and Identification of Experts

The authors included between 10 and 20 experts in the expert consultation to ensure the credibility of the results; more than 20 would not have a significant impact on the results. The authors adopted a nonprobabilistic subjective sampling method, inviting 16 consulting experts from universities and teaching and research institutions. They were mainly engaged in professional research in such disciplines as curriculum and teaching theory, principles of pedagogy, teacher education, and comparative education. Table 3 provides relevant details.

Establishing Indicators of Teaching Model Design

Based on the above components of teachers' teaching mode design, the authors designed an expert consultation tool for teaching mode design components, with specific descriptions for four primary indicators and eight secondary indicators. The researchers selected the impact indicators by consulting experts' opinions, and created online and offline questionnaires . The authors developed the final expert consultation questionnaire for the OBE teaching concept of the student animation course.

Table 3. Specific Information on the Experts Selected for This Study

Serial number	Gender	Title	Serial number	Gender	Title
1	Male	Professor	9	Male	Professor
2	Male	Professor	10	Male	Associate Professor
3	Female	Professor	11	Female	Professor
4	Male	Professor	12	Female	Professor
5	Female	Professor	13	Male	Professor
6	Male	Professor	14	Female	Professor
7	Female	Professor	15	Female	Professor
8	Male	Associate Professor	16	Male	Associate Professor

Delphi Method

The Delphi method (Gray et al., 2022) is a feedback anonymous connotation enquiry method, in which the evaluation criteria are mainly collated for the weights to be determined. The corresponding questionnaires are sent to experts in the relevant fields for scoring, and the results are summarized, collated, and counted upon receipt (Peng & Yu, 2022). The results of the first round are sent back to the experts for their opinion and repeated several times until a consensus is reached. Compared to the expert scoring method, the Delphi method increases the exchange of information between experts and avoids large differences (Manli et al., 2020).

In this study, the authors used the Delphi method to determine the weight of the indicators. Compared with the hierarchical analysis method, the Delphi method does not require the establishment of a more complex matrix for calculation, and, compared with the expert scoring method, it can improve the feasibility of the weights obtained (Ji, 2021). The steps are as follows:

1. Determine all the indicators, clarify the scoring rules, i.e., all the weights add up to one, set up the corresponding questionnaire, select the teaching targets, and distribute the questionnaire.

Count the returned questionnaires and calculate the coefficient of variation C.V of the weights scored by the experts. The coefficient of variation here is set at less than 30% and is considered valid. The formula for calculating the coefficient of variation is as follows:

$$C.V = (SD \div MN) \times 100\% \tag{1}$$

where *SD* denotes standard deviation and *MN* denotes mean.

3. Attach the first research and conduct the next round of questionnaires. Additional questions are asked about the reasons for their scoring for less consistent indicators.
4. Tally the returned questionnaires and here calculate the coefficient of variation of each weight scored by the experts. If all the weights are scored with good consistency, then stop the research on the weights; if there are still weight indicators with poor consistency, then proceed to the third distribution of the questionnaires; if the third returned results still have weights with poor consistency, then remove these weights with poor consistency from them for the next step.
5. Collate the scores collected for the weights, in the form of intervals.

Determination of Objective Weights

In order to compensate for the shortcomings of subjective assignment methods, scholars have proposed different types of objective assignment methods, depending on the field and the value of the scheme attributes. Compared with subjective assignment methods, objective assignment methods have a strong mathematical theoretical basis and are mainly calculated in a more complex mathematical way, but the objective weights obtained from a completely mathematical point of view are likely to result in a lack of flexibility in the weights obtained, which does not allow the actual decision maker to control the actual situation and attribute values (Leow & Neo, 2014).

This paper focuses on objective weighting using the weight determination method in preference-free uncertain multiattribute decision making. The calculation steps are as follows:

1. The decision matrix is normalized using the specific weight transformation method, the decision matrix is classified into benefit type and cost type according to different influencing factors, and different normalization matrix (Equations 2 and 3) are used to process the decision matrix according to different types of influencing factors to obtain the normalized decision matrix:

$$r_{ij}^{L} = \frac{a_{ij}^{L}}{\sqrt{\sum_{m}^{i=1}\left(a_{ij}^{U}\right)^{2}}} \tag{2}$$

$$r_{ij}^{U} = \frac{a_{ij}^{U}}{\sqrt{\sum_{m}^{i=1}\left(a_{ij}^{L}\right)^{2}}} \tag{3}$$

$$r_{ij}^{L} = \frac{i \in I_{1}}{\sqrt{\sum_{m}^{i=1}\left(1 / a_{ij}^{L}\right)^{U}}} i \in I_{2} \tag{4}$$

$$r_{ij}^{U} = \frac{\sqrt{\left(1 / a_{ij}^{L}\right)^{2}}}{\sqrt{\sum_{m}^{i=1}\left(1 / a_{ij}^{U}\right)^{2}}} i \in I_{1} \tag{5}$$

where I_1 and I_2 denote the formulae used for the benefit and cost models, respectively.

2. For attribute u_j, if the deviation value of option x_i from all other options is expressed as $D_{ij}(\omega)$, then it can be defined as follows:

Table 4. Initial Screening of Data From Selected Expert Consultations

Category	Average	Standard deviation
Expert 1	4.86	3.74
Expert 2	4.53	3.25
Expert 3	4.25	3.65
Expert 4	4.81	3.52
Expert 5	4.38	3.14
Expert 6	4.12	3.26

$$D_{ij}(\omega) = \sum_{m}^{k=1} \tilde{r}_{ij} - \tilde{r}_{kj}\omega_j = \sum_{m}^{k=1} d\left(\tilde{r}_{ij}, \tilde{r}_{kj}\right)\omega_j, i \in M, j \in N \tag{6}$$

Further, the authors assume that the following Equation holds:

$$D_j(\omega) = \sum_{m}^{k=1} D_{ij}(\omega) = \sum_{m}^{i=1}\sum_{m}^{k=1} d\left(\tilde{r}_{ij}, \tilde{r}_{kj}\right)\omega_j, j \in N \tag{7}$$

3. It is now necessary to choose the attribute weight vector ω in such a way that the total deviation of all influencing factors for all scenarios is maximized. The deviation function can therefore be constructed by combining the above Equations, as follows:

$$\max D(\omega) = \sum_{n}^{j=1} D_{ij}(\omega) = \sum_{m}^{i=1}\sum_{n}^{j=1}\sum_{m}^{k=1} d\left(\tilde{r}_{ij}, \tilde{r}_{kj}\right)\omega_j \tag{8}$$

4. Solving for weight ω, which is equivalent to solving the following single-objective optimization problem under a range of treatments, gives:

$$\omega_j = \frac{\sum_{\mathrm{m}}^{i=1}\sum_{m}^{\mathrm{k}=1} d\left(\tilde{r}_{ij}, \tilde{r}_{kj}\right)}{\sum_{m}^{i=1}\sum_{n}^{j=1}\sum_{m}^{k=1} d\left(\tilde{r}_{ij}, \tilde{r}_{kj}\right)} \tag{9}$$

EXPERIMENTAL ANALYSIS

Preliminary Statistics and Processing of Recovered Data

The experts scored the importance of each indicator and made comments and suggestions on each primary and secondary indicator, and then conducted descriptive analyses of the mean, median, full frequency, standard deviation, coefficient of variation, and other key indicators of the primary and secondary indicators (Ma, 2018).

If an indicator met all three criteria, it would be included; if an indicator did not meet one or two of the criteria, then it would be included or not based on expert opinion; if an indicator did not meet any of the three criteria, it would be excluded. Table 4 provides information on some of the experts' screening data.

Figure 4. Comparison of the Initial Screening of the Six Expert Consultation Data

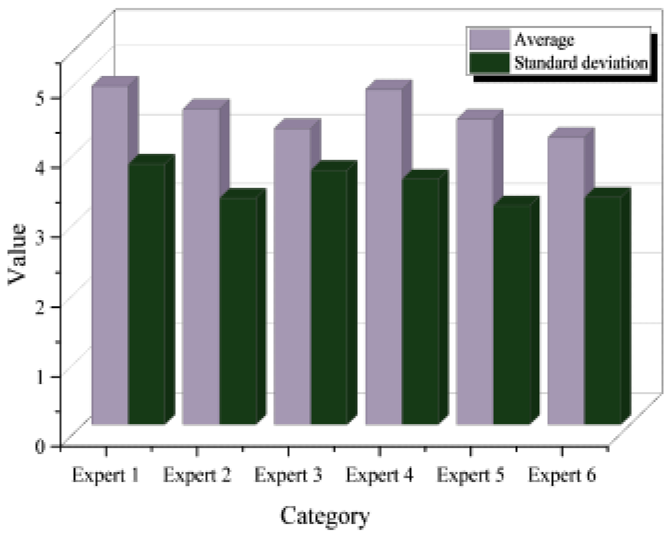


Figure 4 shows the initial screening comparison effect of these six expert consultation data.

The data in Figure 4 evidence that all 12 indicators met the above criteria and reached the initial availability. However, whether these available indicators could reflect the true opinions of the experts needed further analysis.

Analysis of the Concentration of Experts' Opinions

In the process of applying the Delphi method, the reliability of expert advice is reflected in four main aspects: 1) The degree of authority of experts; 2) the motivation of experts; 3) the degree of concentration of expert advice; 4) the degree of coordination of expert advice. Among them, the degree of concentration of experts' opinions is the most important factor influencing the results of expert consultation, which can be expressed by the mean of importance assignment M and the frequency of full score K. The larger the value of M, the more important the indicator is.

Based on the statistical results, Table 5 shows the basic situation of the first round of expert consultation.

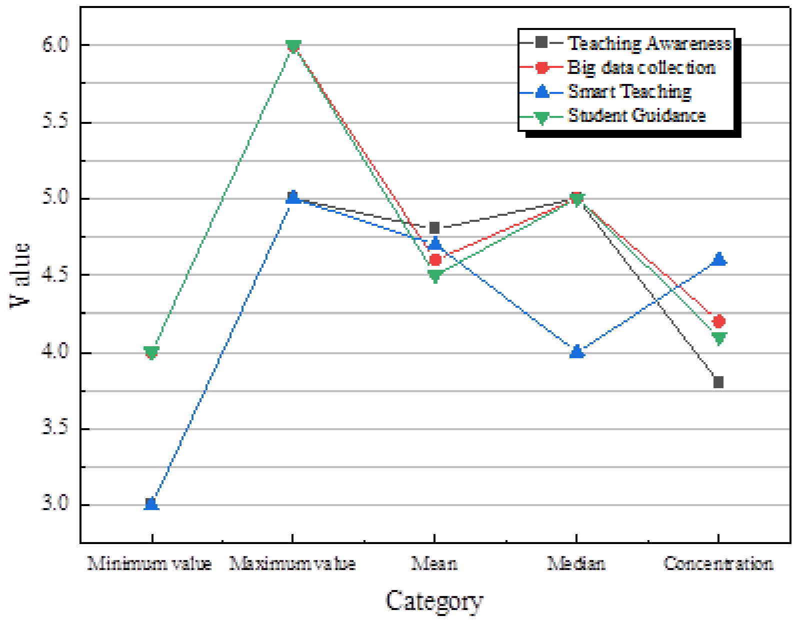
Figure 5 shows the comparative effect of the experts' opinions on the evaluation of the primary indicators.

As Figure 5 highlights, the experts' opinions are more concentrated on the first level components, with three of the four indicators scoring 80% or more. The average value of the first level indicators

Table 5. Experts' Opinions on the Indicators of the First Level of Evaluation of Teaching Model Design

Category	Minimum value	Maximum value	Mean	Median	Concentration
Teaching awareness	3	5	4.8	5	3.8
Big data collection	4	6	4.6	5	4.2
Smart teaching	3	5	4.7	4	4.6
Student guidance	4	6	4.5	5	4.1

Figure 5. Comparison of Experts' Opinions on the First-Level Indicators of the Evaluation of Teaching Model Design



is above 4.5 points. The above analysis shows that most of the experts are in agreement on the first level component indicators and agree on the importance of each first level component indicator.

The frequency analysis clearly shows the basic information of the experts' opinions, and it is possible to find out the full score rate of the experts' opinions and the data of the options with large differences. Table 6 shows the results of the frequency analysis of the indicators of the secondary elements that make up the design of the teaching model for animation courses.

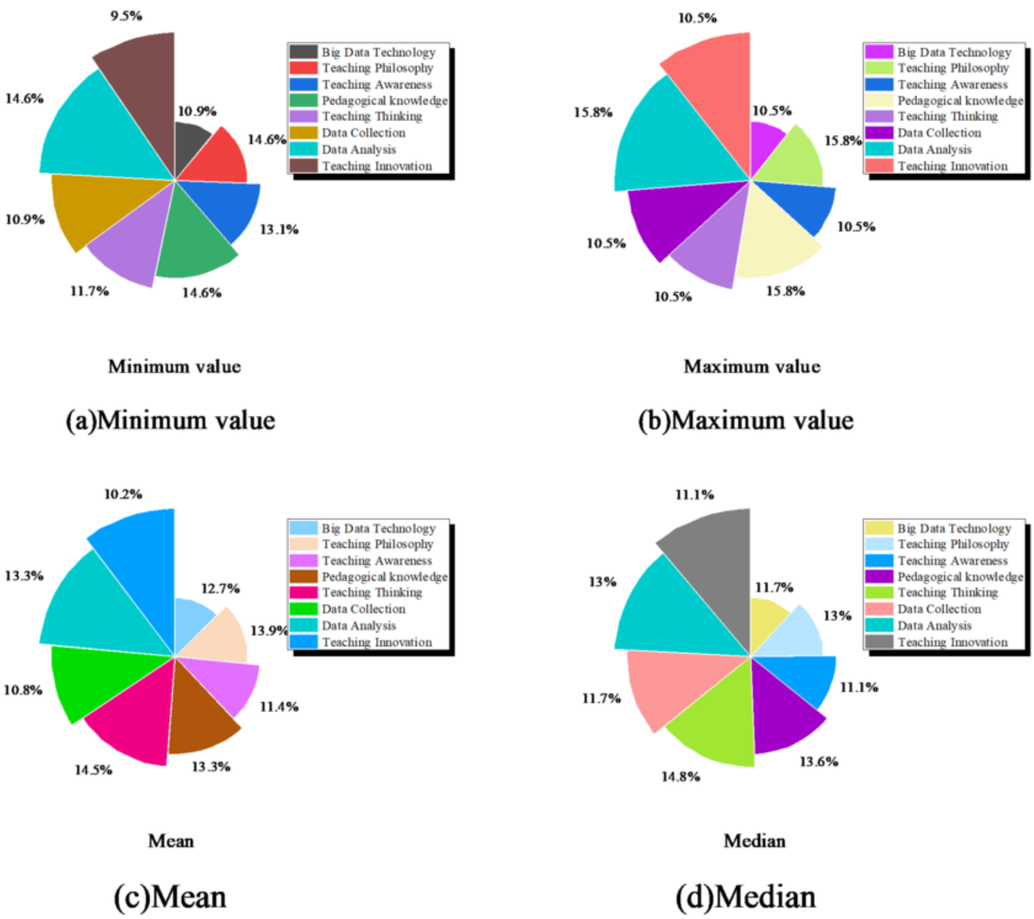
Figure 6 illustrates the results of the visual comparison of the secondary indicator data for the design of the animation course teaching model.

In terms of averages, the experts' opinions on the secondary element indicators are relatively concentrated, with all but one indicator having an average value of 1.8 or more. Figure 7 shows a comparison of the concentration data for the secondary indicators.

Table 6. Data on Secondary Indicators of the Design of Teaching Models for Animation Courses

Category	Minimum value	Maximum value	Mean	Median	Concentration
Big data technology	1.5	2	2.1	2.5	1.9
Teaching philosophy	2	3	2.3	2.6	2.1
Teaching awareness	1.8	2	1.9	2	1.8
Pedagogical knowledge	2	3	2.2	2.1	2.2
Teaching thinking	1.6	2	2.4	2.4	2.4
Data collection	1.5	2	1.8	2.3	1.9
Data analysis	2	3	2.2	2.1	2.1
Teaching innovation	1.3	2	1.7	2.4	1.8

Figure 6. Visual Comparison Results of the Data for the Secondary Indicators for the Design of the Teaching Model of the Animation Course: (a) Minimum Value, (b) Maximum Value, (c) Mean, and (d) Median



Analysis of the Process and Results of the Second Round of Expert Consultation

The results of the first round of expert consultation showed that the convergence of experts' opinions was not very good, mainly reflected in the coordination coefficient of 0.168. Therefore, based on the opinions and suggestions of most experts, the authors developed the second round of expert consultation questionnaire after careful revision and adjustment of the components of the teaching mode design of the animation course. In the second round of consultation, the researchers sent the questionnaire to the 16 experts consulted in the first round using the Questionnaire Star tool based on the MOOC platform, and received timely responses from these experts. Therefore, the positive coefficient of the second round of experts was still 100%, and, once again, proved that the experts consulted were concerned about the design and evaluation of the teaching mode of the animation course.

In order to further determine the degree of consistency of the 16 experts' opinions, a further measure of the degree of coordination of the experts' opinions is the coordination coefficient. The coefficient of coordination ranges from 0 to 1, and the closer to 1, the higher the degree of coordination of all experts' opinions. Table 7 shows the degree of coordination of experts' opinions on the nonparametric test.

Figure 7. Comparison of Secondary Indicator Concentration Data

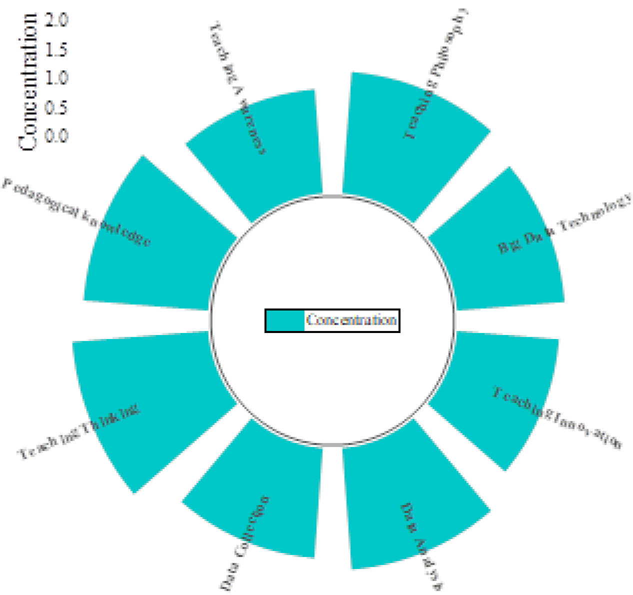


Table 7. Level of Coordination Between the Two Rounds of Expert Consultation

Category	Coordination factor	Cardinality	Number of indicators
First round	0.168	56.30	16
Second round	0.631	206.54	16

The coordination coefficient for the first round is 0.168. The coordination coefficient for the second round is much higher, at 0.613, and the expert opinions in this round are basically consistent. The difference between the 16 experts' opinions in these two rounds is significant, indicating that the results of both rounds are highly credible. In summary, the 16 experts reached a high level of agreement on the design and evaluation of the teaching model of the animation course, indicating the desirability of the research findings.

The degree of expert authority, which refers to the strength of an expert's authority on a research question or field, has a significant impact on the reliability of the evaluation, and therefore the degree of expert authority is used as an important indicator of the reliability of expert advice in the Delphi method. Table 8 shows the frequency distribution of experts' judgement bases in this study, as well as the coefficients assigned to experts' judgement bases and their degree of influence in the above section, which can be calculated for 16 experts.

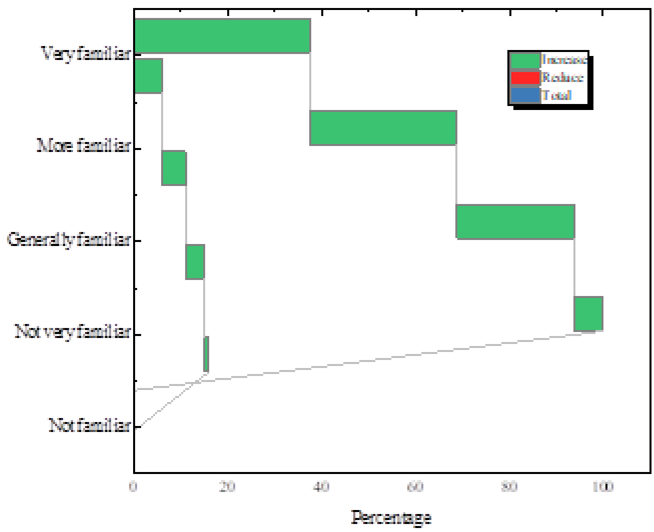
Figure 8 shows the results of the visual comparison of the expert familiarity discrimination data.

Evidence shows that, in the animation course teaching mode design and effect evaluation method from the perspective of big data, the experts are very familiar with the indicators and evaluation scores at all levels affecting the course teaching mode, so the experts' scoring is more scientific. In the animation course teaching mode design and effect evaluation method, the authors combined the scores of 16 experts on 12 indicators through two rounds of expert consultation, obtained the indicators affecting the teaching mode design and their weighting order, and evaluated and analyzed their teaching design effects. The obtained influential indicators laid the foundation for the further

Table 8. Expert Familiarity Discriminatory Data

Category	Percentage	Frequency
Very familiar	37.5	6
More familiar	31.25	5
Generally familiar	25	4
Not very familiar	6.25	1
Not familiar	0	0

Figure 8. Visual Comparison of Expert Familiarity Discriminant Data



development of the animation client talent teaching model in the future and showed the effectiveness of the method the authors proposed in this paper.

In this study, the authors used the MOOC platform from the perspective of big data to analyze the current teaching situation and innovative process of animation courses, and proposed a hybrid animation course teaching method. The results of a survey the authors conducted wiht 686 primary and secondary school teachers showed that this method has better effects than traditional teaching methods, improves students' initiative in learning animation courses, and greatly enhances their acceptance of learning animation courses. Subsequently, the authors analyzed the concentration ratio of experts' opinions, which showed that experts' opinions on the first level indicators were consistent, and so was the importance of each level indicator. Finally, through two rounds of expert consultation, the authors obtained the indicators and their weight ranking that affect the design of teaching modes, and evaluated and analyzed the effectiveness of their teaching design. This study provides new ideas and methods for the design of animation course teaching modes, but still some issues need further exploration in existing research. For example, this study only focused on primary and secondary school students, and further exploration is needed in terms of learning outcomes for college students and adults. In addition, this study only used the MOOC platform for data collection and analysis, while comparisons between other online education platforms and traditional classroom education are also worth studying. In addition, in terms of inspiration from educational practice, the authors proposed a more personalized and project-based learning approach, but how to apply this approach to learning in other fields still needs to be explored.

Further research can focus on the impact of different teaching methods and techniques on the learning outcomes of animation courses. The implications of this study for educational practice include more personalized and project-based learning methods, the importance of teacher professional development, and the potential of big data and artificial intelligence in education. In terms of limitations, this study only focused on a single teaching mode and lacks comparison with other teaching methods. Future research can explore the differences between different teaching methods and technologies. In the future, the specific content and teaching methods of animation course teaching mode design can be compared and analyzed with learners in different fields and age groups.

In this research, the authors addressed the challenge of designing and evaluating an effective teaching model for animation courses. They applied the OBE concept to the design of the teaching model, which emphasizes the improvement of students' subjectivity and practical abilities. In addition, the authors explored the use of MOOC platforms and big data analysis in the teaching process. The contribution of this research is the development of a hybrid teaching method for animation courses based on the combination of OBE and MOOC, which the authors found to be more effective than traditional teaching methods in terms of enhancing students' learning autonomy and acceptance of animation courses. Moreover, the results of this study can offer practical advice for educators who are interested in teaching animation courses through the hybrid method. Specifically, instructors should pay close attention to the design of the primary and secondary indicators used to evaluate the teaching model, as well as the level of agreement among the experts involved in the evaluation process.

CONCLUSION

The development of Internet technology has brought a great impact on the traditional teaching model of animation courses, and the OBE teaching model emphasizes learning outcomes and learning evaluation, which means that it focuses on the effectiveness of the teaching process (Wu & Tu, 2022). Under this teaching model, the emphasis on the role of the student subject is an important criterion for educational innovation in the new era. In this paper, starting from the OBE teaching mode, based on the MOOC platform from the perspective of big data, the authors explored the indicators at all levels affecting the teaching mode of animation courses by establishing online and offline questionnaires (Fu, 2021). When using the Delphi method to determine the weights of indicators, the evaluation criteria are collated for the weights to be determined, and the corresponding questionnaires are scored by experts, and the results are summarized, collated, and counted upon receipt. The experimental results showed that, in the animation course teaching mode design and effect evaluation method, through two rounds of expert consultation, the authors synthesized the scores of 16 experts on 12 indicators, obtained the indicators affecting the teaching mode design and their weighting order, and evaluated and analyzed the teaching design effect. As the data sources in this paper were relatively limited, more data are needed in the study of the influencing indicators. Future research will be oriented to more objects and devoted to finding a more perfect teaching mode and evaluation scheme for animation courses. This study has certain reference value for exploring the teaching mode design and effectiveness evaluation methods of animation courses. At the same time, this study emphasizes the profound impact of Internet technology on the education industry, as well as the emphasis on learning outcomes and evaluation under the OBE teaching model. Through practice, the authors verified the effectiveness of hybrid OBE and MOOC teaching models in improving students' learning effectiveness and initiative. Further research on this topic can focus on exploring the impact of different teaching approaches and technologies on the learning outcomes of animation courses. The implications of this study on education practice include the need for more personalized and project-based learning, the importance of teachers' professional development, and the potential of big data and artificial intelligence in education.

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DATA AVAILABILITY

The Figures and Tables used to support the findings of this study are included in the paper.

CONFLICTS OF INTEREST

The authors declare that they have no conflicts of interest.

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CORRESPONDING AUTHOR

Correspondence should be addressed to Yi Zhang (zz1991zy@zzu.edu.cn)

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