Hindawi
Security and Communication Networks
Volume 2023, Article ID 9761562, 1 page
https://doi.org/10.1155/2023/9761562

Retraction

Retracted: The Impact of Digital Technology on the Optimization of Higher Education Teaching Models in an Epidemic Environment

Security and Communication Networks

Received 8 August 2023; Accepted 8 August 2023; Published 9 August 2023

This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

(1) Discrepancies in scope
(2) Discrepancies in the description of the research reported
(3) Discrepancies between the availability of data and the research described
(4) Inappropriate citations
(5) Incoherent, meaningless and/or irrelevant content included in the article
(6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

[1] Y. Zhu, "The Impact of Digital Technology on the Optimization of Higher Education Teaching Models in an Epidemic Environment," *Security and Communication Networks*, vol. 2022, Article ID 5301459, 9 pages, 2022.

Hindawi
Security and Communication Networks
Volume 2022, Article ID 5301459, 9 pages
https://doi.org/10.1155/2022/5301459

Research Article

The Impact of Digital Technology on the Optimization of Higher Education Teaching Models in an Epidemic Environment

Yuanyuan Zhu [1,2]

[1] *College of Education, Shanghai Normal University, Shanghai 200233, China*
[2] *Institute of Higher Education, Jiangsu Normal University, Xuzhou, Jiangsu 221116, China*

Correspondence should be addressed to Yuanyuan Zhu; zhuyuanyuan@jsnu.edu.cn

Received 14 March 2022; Revised 8 April 2022; Accepted 15 April 2022; Published 28 May 2022

Academic Editor: Muhammad Arif

The Corona Virus Disease 2019 epidemic broke out in 2020, and digital technologies pervaded all aspects of people's lives, resulting in a significant shift in how education is delivered. The importance and role of digital technologies and online learning are highlighted in this paper, which examines the challenges posed by the sudden epidemic crisis to higher education institutions, analyses the factors that universities must consider in order to effectively create flexible learning pathways, and examines the challenges posed by the sudden epidemic crisis to higher education institutions. In the postepidemic era, the use of the Internet and online teaching platforms by university faculty to integrate online and offline teaching has not only facilitated the construction of "golden courses" but also added impetus to teaching reform, and digital technology-based teaching models have provided higher education practitioners with the opportunity to rethink scholarship and innovative teaching. In this paper, we propose a personalized learning resource recommendation system that includes user profiles to fully explore and analyze users' learning behaviors and cognitive characteristics and enhance the depth and breadth of personalized education with the help of the Internet and artificial intelligence technologies in order to provide meaningful information and thoughts for higher education institutions to discuss and adapt to the education model in the postepidemic era. The goal is to provide useful information and ideas for higher education institutions to discuss and adapt to the postepidemic education paradigm.

1. Introduction

The level of higher education is an important indicator of a country's development level and development potential, and how to explore an efficient teaching model is a major educational issue common to mankind. The abrupt emergence of a new coronavirus epidemic has increased the difficulties of higher education teaching reform [1–3], and developing a set of contingent and efficient teaching models to enhance higher education development in the postepidemic age is a big problem. Although the offline-online fusion teaching model was also partially applied in the preepidemic era, the arrival of the postepidemic era has greatly accelerated the popularity and application of the offline-online fusion teaching model for higher education development. Offline integrated online teaching fully demonstrates the charm of the information technology era, which provides new opportunities and chances for the development of higher education.

The OECD estimates that COVID-19 has enabled more than 180 countries (regions) in the world, with more than 90% of learners and over 1.5 billion students affected by school closures to have to adapt to the new blended learning model in a very short time. To avoid a decline in the quality of education in the online classroom environment, teachers are looking for ways to try to maintain the same depth of contact with students as in the face-to-face classroom [4–6]. In the short term, a complete shift from face-to-face to distance learning is a desperate attempt to force the closure of schools. However, in the long run, higher education institutions should adopt a multipronged strategy to establish a flexible and feasible educational system that is easy to replicate and implement and that is capable of achieving comprehensive and effective educational practices in the face of unexpected crises, combining the development of student's skills with the development of their intellectual abilities, both to promote students' employability, productivity, and health and to meet the country's overall future development needs for talent development and reserves. It is impossible to predict whether the global epidemic will become a "black swan" event that will trigger the transformation of higher education [5], but it is important to realize that this is not a once-in-a-lifetime crisis. Higher education institutions and administrative oversight should take this opportunity to reassess the strengths and weaknesses of existing education systems, the challenges ahead, the importance of educational contingency planning and risk management, the urgency of supporting innovative delivery methods, and the need to provide flexible learning assessments and entry requirements. At the same time, this health crisis provides an opportunity for higher education practitioners to rethink academics and envision future educational possibilities [7]. As shown in Figure 1, the keywords COVID-19 and higher education teaching are searched hot on Google, and it can be found that there is some correlation between the two.

Education must be modernized, and it is becoming increasingly intertwined with current technologies. However, it is impossible to overlook the fact that digitalization is both a solution and a new issue. The classroom does not merely change from a physical to a virtual environment when students learn online; as the interactive space shifts, so does the way teaching and learning take place. Teachers and students are faced with a new beginning in how to teach and learn on digital platforms. Learning with digital applications requires teachers to do more than deliver learning content via videoconferencing or online classrooms [8–10]; it also requires digital technology and the support of multimedia elements. It is necessary for teachers to participate in training to learn and update their digital skills beyond the professional academic competencies required. At the same time, student collaboration on digital platforms is crucial to the success or failure of teaching and learning activities. Digital learning platforms need to have elements that stimulate students' interest and motivation to learn [11].

The tailored recommendations on most online education platforms are studied and modelled based on the characteristics of the users. For example, personalized feature information such as users' learning styles and learning interests is used to build recommendation models. However, the results of such recommendations are often crude and hardly satisfactory and are generally suitable for some simple recommendations. In recent years, some researchers have started to try to use users' behavioral feature information to analyze the similarity between users. By calculating the similarity of users' learning behavior sequences, user-based collaborative filtering recommendation modeling is used [9]. However, these studies focus more on the user's feature information and neglect the mining and analysis of learning resources. In this paper, we propose a hybrid recommendation system for personalized learning resources based on learning styles, resource preferences, and behavioral sequences, which combines learning styles and resource

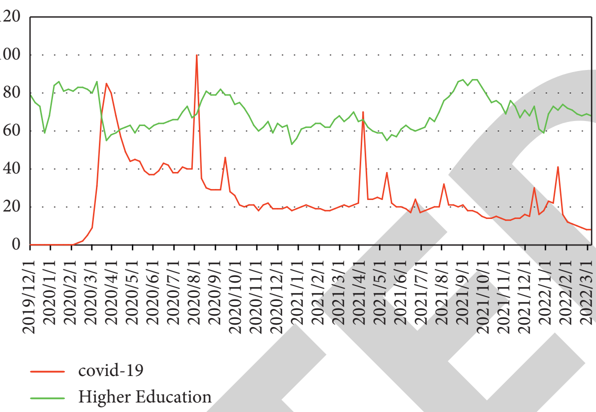

Figure 1: Keywords new coronavirus and higher education teaching on Google search heat.

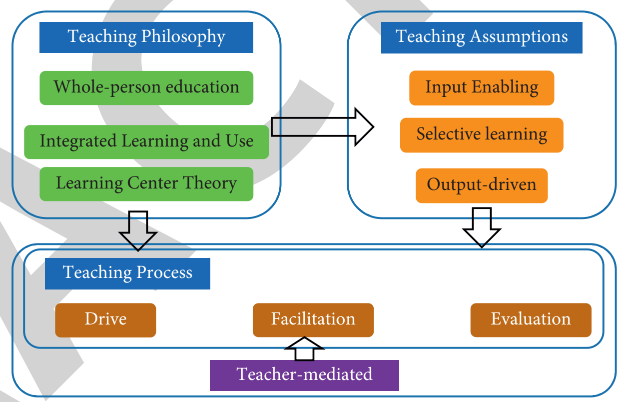

Figure 2: Traditional higher education model.

preferences to generate personalized portraits for users while fully utilizing their behavioral feature information and also provides users with learning feedback and personalized learning material recommendation services, thereby enhancing the use of digital technology.

The following is a summary of the research: Section 2 discusses the related work; Section 3 discusses the methodology. In Section 4, experimental results of the proposed concepts. Finally, the conclusion brings the paper to a finish in Section 5.

2. Related Work

2.1. Traditional Higher Education Teaching Model. The traditional teaching mode Chinese traditional teaching in Figure 2, also known as offline teaching mode, is centered on teachers, classrooms, and teaching materials, with classroom education as the mainstay [12–14], and teachers use hard and indoctrination teaching methods to disseminate knowledge, and the teaching process is divided into three stages: preclass preparation, classroom lectures, and postclass consolidation, with students acquiring information through teachers' dictation and board books, as well as consolidation through postclass exercises, and teachers understanding students' mastery of the teacher understands the students' mastery of what they have learned based on the students' feedback and adjusts the teaching strategy appropriately in order to achieve the educational purpose. In other words, offline teaching is a teaching mode in which the teacher is the leader and the students passively receive knowledge [13]. Advantages of traditional education include more time and opportunities for students to communicate and interact with one another, and they influence and progress together while exercising their language expression and interpersonal skills, which aids in the development of students' personalities and abilities. And for courses like the daily patriotic education classes, the traditional education mode has more advantages in that students can not only learn theoretical knowledge but also deeply understand patriotic feelings through practice.

2.2. Higher Education Teaching Model in the COVID-19. The "New Coronation Epidemic" is a dividing line in the world of basic education, which divides world basic education into "preepidemic basic education" and "post-epidemic basic education." It divides the world's basic education into "preepidemic basic education" and "post-epidemic basic education. The epidemic has broken the old traditional educational order and pattern, rebuilt a new systematic order and pattern, and pushed the future pattern and model of basic education toward a deep integration in many aspects. The epidemic is a challenge and an opportunity for modern education. Although comprehensive online teaching has encountered many difficulties and setbacks, it has enabled teachers and students to appreciate the charm of information technology, and the use of online teaching in teaching has become a major trend. Although online and offline integrated teaching has promoted the change of university teaching, the diversification of teaching, and provided students with more colorful ways to learn the curriculum, how to build a more complete online and offline integrated teaching, help students build their own knowledge system [15–17], and enable students to carry out deep learning and cultivate students' ability of lifelong learning is still a problem worth thinking about for the majority of front-line teachers. According to Bloom's taxonomy of educational objectives, we know that educational objectives are divided into two dimensions: the knowledge dimension and the cognitive history dimension [18]. The cognitive journey dimension is divided into six levels: knowledge, comprehension, application, analysis, evaluation, and creation. The theory of "distributed cognition" suggests that when technology develops to a certain level, a part of our brain will be completely freed up, such as the memory part. Therefore, the simple presentation of knowledge in the traditional classroom no longer meets the needs of the times, and the cultivation of students' thinking skills will be the focus of education in the new era. In the context of the postepidemic era, in order to more effectively cultivate students' cognitive and thinking abilities, teachers' teaching should base their scientific teaching design on Bloom's six levels of educational objectives and make reasonable arrangements for the lecture content according to the nature and characteristics of the curriculum.

3. Methodology

3.1. Model Structure. A bottom-up data layer, a data analysis layer, and a recommendation calculation layer make up the planned personalized learning resource recommendation system, which is applied to the architecture of an online education platform that focuses on artificial intelligence classes, as shown in Figure 3.

3.2. Data Layer

3.2.1. User Database. The user database stores the user's characteristic information, including personalized characteristic information and behavioral characteristic information. Personalized characteristic information is the information inherent to the user and does not change over time or changes slowly. Typical personalized characteristic information includes the user's age, gender, major, and other basic information, such as learning style and other course pretest information. Personalized characteristic information is represented in the form of data as static data. Behavioral information is information that has changed significantly over time, for example, login time, number of clicks, postings, and so on. This type of information is dynamic in the form of data. In this study, behavioral characteristic information is classified according to the following three learning styles of users:

(1) Independent learning, such as watching videos, browsing learning materials, and so on.
(2) Reflective learning, such as submitting assignments, viewing assignment correction results, and so on.
(3) Communication feedback, such as leaving messages in discussion forums, and so on.

3.2.2. Resource Library. The resource library consists of knowledge materials, learning materials, and tag materials. Knowledge materials include knowledge blocks and knowledge points. In the implemented pattern recognition case [19], the division of chapters and the medium and small headings are used as knowledge blocks, and the theorems, algorithms, mathematical and theoretical terms, and so on, appearing in the content of each chapter are used as knowledge points [20, 21]. Learning material refers to the content material after web crawling with knowledge blocks and knowledge points as keywords in the knowledge material and doing some manual screening. Tag set refers to the general description used in the system to outline the content and form of the learning material. The tags not only give users a quick and easy overview of the learning materials, but they also allow them to be turned into appropriate text fields for deep data mining and analysis. Seven sorts of tags are designed in terms of both content and form in the implemented pattern recognition case:

(1) Content:

Knowledge blocks (tag values: middle heading, subheading); knowledge points (tag values: algorithms, theorems, combining terms).

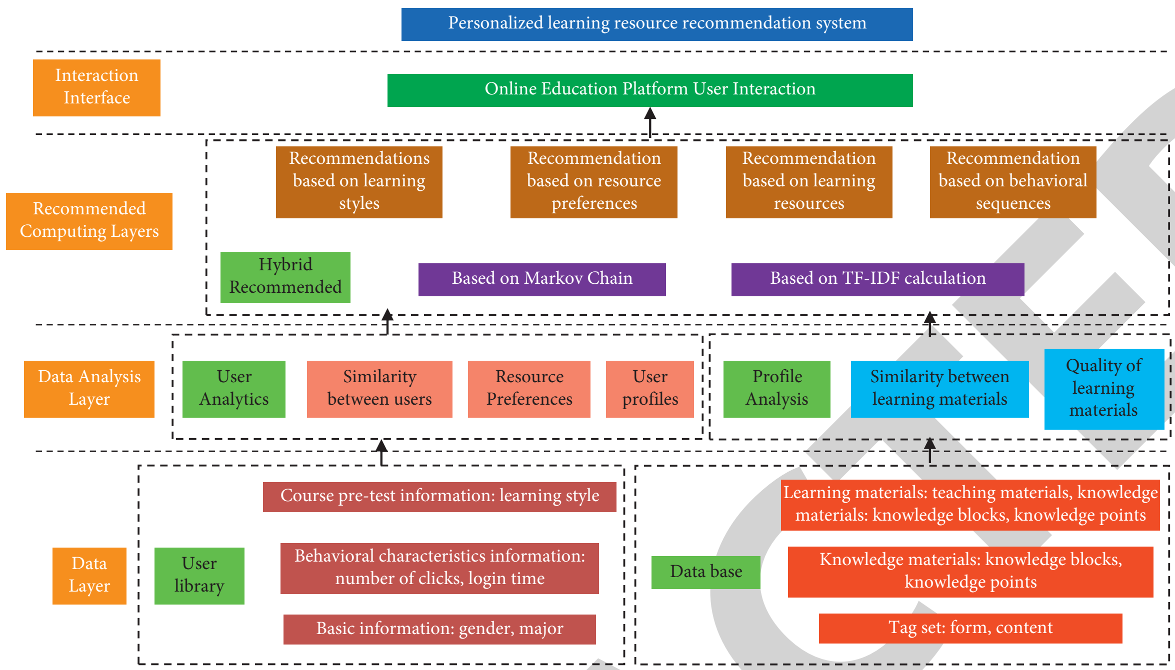

Figure 3: Model architecture.

(2) Form:

Language (tag value: Chinese, English); category (tag value: derivation, implementation, summary, promotion); carrier (tag value: text, picture, video); dataset (tag value: MNIST, sklearn data, other); programming language (tag value: java, c++, python, other).

3.3. Data Analysis Layer

3.3.1. User Analysis. The system quantifies, counts, and models the personalized characteristic information and behavioral characteristic information of users to mine and analyze them, including similarity analysis among users, resource preference analysis, and user portraits. Similarity analysis among users is the basis for user recommendation modeling. It calculates the degree of correlation between users through their characteristic information to determine the similarity between users, calls similar users "neighbor users," and then recommends the learning resources chosen by "neighbor users" to the current users. Resource preference refers to the user's preference and preference for the content and form of learning resources. For example, some users prefer text-based learning materials, while others prefer video-based learning resources [22]. In this system, the TF-IDF algorithm is used to calculate the weights occupied by the tag values of each category of tags under the user so that the resource preferences of the user can be derived. User profiling is a user model built on a series of real data. It can describe the learning characteristics of users from multiple perspectives. Unlike most online education platforms that only use personalized feature information to build user profiles, this system combines both personalized feature information of users and behavioral feature information to quantitatively and qualitatively build personalized profiles of users. For example, the learning style is derived from the user's course pretest information; the common module sequence, knowledge interest point, knowledge difficulty point, assignment details, and so on are derived from the user's browsing time, frequency of browsing learning materials, and other behavioral characteristics. Users can understand and master their learning situation through personalized portraits and easily adjust their learning strategies.

3.3.2. Data Analysis. The number of tags, clicks (reads), comments, and so on is used as the attribute features of the learning materials. By quantifying, counting, and modeling the attribute characteristics of learning materials, the system performs similarity analysis and quality analysis of learning materials. Similarity analysis among learning materials is the basis of modeling based on learning resource recommendations. It uses the labels of learning materials as features to calculate the degree of correlation between learning materials so as to determine the similarity between learning materials, calls the similar materials "neighbor materials," and then recommends the "neighbor materials" to the current user [23]. The quality analysis of learning materials is mainly through the statistical analysis of attributes such as the number of clicks (reads) and comments, which can filter out poor-quality content to a certain extent.

3.4. Recommendation Calculation Layer

3.4.1. Recommendation Based on Learning Style. The online learning platform analyzes the learning style of users by

Table 1: Explicit classification of learning styles.

Style dimension	Dimensional classification	Characteristics	Related recommendations
Information processing	Active	Prefer to verify ideas through experiments, do first and think later, prefer discussion and teamwork	For example, discussion forums, forums
	Contemplative	Prefer to learn new things by thinking, think before doing, prefer to think and work independently	For example, blogs, journals
Information perception	Perceptive	Prefer to learn by example, memorization	More concrete examples (e.g., algorithm applications)
	Intuitive	Prefer abstraction, derivation	More abstract derivations (e.g., algorithm extensions)
Information input	Verbal	Prefer explanatory text	PPT, literature
	Visual	Prefer pictures, videos, and so on	Videos, mind maps
Information comprehension	Integrated	Understand in general before going deeper	More "up and down" labeled courses or knowledge navigation
	Sequential	Learn step by step in the sequence	More general outlines

guiding them to complete a precourse learning assessment task with good credibility. In turn, the system recommends learning resources according to the user's learning style. The paper uses four dimensions of the Felder–Silverman model to classify users' learning styles, which are information processing, information perception, information input, and information understanding, as shown in Table 1.

3.4.2. Recommendations Based on Behavioral Sequences. Although recommendations based on users' personalized feature information are widely used, such recommendations are often coarse. Therefore, such methods are generally suitable for simple recommendations, while it is difficult to obtain satisfactory results for more complex recommendation tasks. In recent years, some studies have started to try to analyze the similarity between users by using their behavioral feature information. The study of behavioral data for web learning is the basis for improving the stability of user similarity calculation. Calculation of behavioral sequence similarity: the behavioral sequences of users are represented by a finite set S:

$$\{(z_1, y_1), (z_2, y_2), \ldots, (z_n, y_n)\}, n \geqslant 2, \tag{1}$$

where (z_i, y_i) denotes the ith element pair, z_i denotes the access module, and y_i denotes the corresponding operation, which is recorded in the set sequentially in the order of behavior occurrence. For the sake of concise description, the string (z_i, y_i), which consists of elements connected in the element pair (z_i, y_i), is denoted by s_i and called the user's ith state string. The state sequence is a string formed by linking the elements in each element pair in the behavior sequence in turn. For example, the state sequence of user S can be expressed as $s_1, s_2, \ldots, s_n$ by the state string, which is denoted as $S = s_1, s_2, \ldots s_n$. The state subsequence of state sequence S is defined as $S^{(i)} = s_{n_1}, s_{n_2}, \ldots s_{n_i}$, where $1 < n_1 < n_2 < \ldots < n_i < s$. Let the state sequences of users A and B be A and B, respectively; then the similarity of the behavioral sequences is given by the following formula:

$$\begin{aligned} \text{sim} &= \alpha \times \text{sim}_{\text{seq}}(A, B) + \beta \times \text{sim}_{\text{trans}}(A, B) \\ &\quad + \gamma \times \text{sim}_{\text{value}}(A, B), \end{aligned} \tag{2}$$

where $\alpha + \beta + \gamma = 1, \alpha \geq 0, \beta \geq 0, \gamma \geq 0. \text{sim}_{\text{seq}}(A, B) = \text{im}_{\text{axs}} + l, \text{sim}_{\text{trans}}(A, B) = \varphi/(s-1) + (l-1), \text{sim}_{\text{value}}(A, B) = |A \cap B|/|A \bigcup B|$ denote the state value similarity, state transfer similarity, and state order similarity, respectively.

3.4.3. User Similarity Calculation Based on Time Decay Effect. Users' learning behaviors at different time periods have different contributions to predicting their learning behaviors. Generally speaking, behaviors that occur closer in time better reflect users' learning interests and contribute more to the similarity between users. To increase the importance of recent behavior sequences for similarity calculation, the temporal weight function WT is introduced.

$$\text{WT}(A, S_i) = (1 - a) + a\frac{D_{A,S_i}}{L_A}, \tag{3}$$

where S_A is the set of all behavior sequences of user A; D_{A,S_i} denotes the time interval between the behavior sequence generated by user A and its earliest generated one; L_A denotes the time span of user A's behavior sequence; and $\alpha \in (0, 1)$ is the weight growth index. Therefore, the user similarity between users A and B based on the time decay effect is calculated as follows:

$$\text{sim}(A, B) = \frac{\sum_{S_i \in S_A}\left[\left(W(A, S_i) + W(B, S_j)\right)/2\right] \cdot \text{sim}(S_i, S_j)}{|S_A| \cdot |S_B|}. \tag{4}$$

When analyzing the relationship between users, it is not enough to consider behavioral similarity alone. There are many reasons for extremely high similarity; for example, differences in users' long-term behavior cannot be observed in a relatively short period of time. However, a more accurate and stable description of the relationship between users is needed in practical applications. For this reason, this paper proposes the concept of the correlation coefficient (i.e., by analyzing the change of similarity over a period of time); the similarity between users in that time period is obtained. Assuming that the average similarity is sim_{avg} and the variance is sim_{dx}, the correlation coefficient (RC) can be calculated by the following equation:

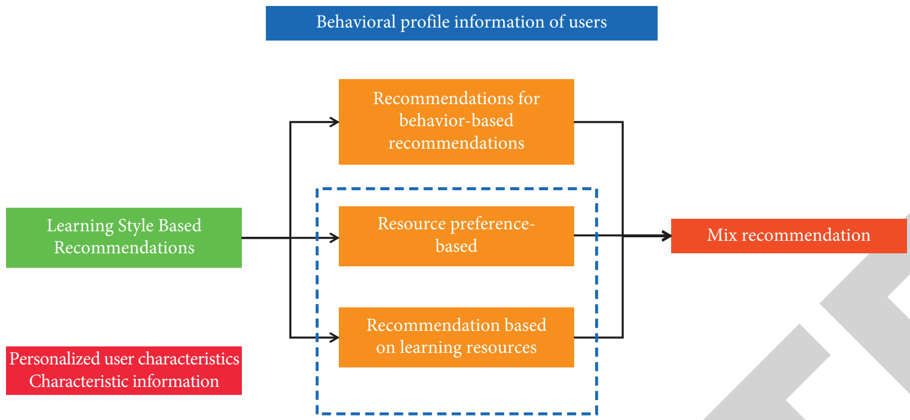

Figure 4: Mix recommendation.

$$RC = \frac{\mathrm{sim}_{\mathrm{avg}}}{\mathrm{sim}_{\mathrm{dx}}}. \quad (5)$$

Therefore, the more similar the relationship between two users is, the greater the change of average similarity; conversely, the smaller the change of average similarity. In order to solve the problem that the traditional nearest-neighbor collaborative filtering recommendation is difficult to meet the real-time demand of the system due to the decrease of the search timeliness caused by the expansion of the user scale, the system first uses the k-means algorithm to cluster the users, then calculates the behavioral sequence similarity in the clustering space of the users, and finally, according to the identified "neighbor users," recommends the learning resources selected by them to the current users according to the recommendation system based on resource preference: The TF-IDF algorithm calculates the weight size of the tag value of each category of tags under the user to obtain the user's resource preference and then gets the basis for learning resource recommendation. For example, for users who prefer text categories, the system recommends more learning materials for text carriers to them.

3.4.4. Recommendation System Based on Learning Resources. The similarity between learning materials is calculated through tags, and the similar materials are called "neighbor materials," and then the "neighbor materials" are recommended to the current user. Since each recommendation method has its own advantages and disadvantages and is suitable for specific scenarios, and since the process of online learning is a dynamic process that is constantly changing, considering only one recommended method for learning resource recommendation may not necessarily meet the actual application situation.

Figure 4 depicts the hybrid recommendation method. As a result, a hybrid recommendation mechanism based on the four strategies listed above is proposed. At the early stage of course learning, users' learning style is obtained based on their precourse learning assessment, and the learning style-based method is used to recommend learning materials; as users' learning time increases and interaction increases, users' learning behavior is mined and analyzed, and the learning behavior-based method is used to recommend learning materials. It is decided to use a collaborative filtering recommendation based on resource preference as the main recommendation and learning resource recommendation as a complement. Figure 5 depicts the text processing strategy used in this paper.

4. Experiments and Results

4.1. Experimental Setup. The compute nodes of the server cluster are used in the experiments in this chapter. The whole cluster contains one 2U (U as height unit) management node mu01, eight 4U compute nodes cu01-cu08 (each compute node is equipped with one dual-core NVIDIA K8024G graphics GPU), one IO storage node oss01, one InfiniBand switch, and one Gigabit Ethernet switch. Python version 3.6 was chosen as the language and TensorFlow version 1.13.1 was used as the deep learning framework.

4.2. Dataset. This recommendation algorithm dataset was chosen from a Chinese online education system's backend data collecting. According to the needs of the subject, two datasets are selected: the course tags dataset (tags) and user ratings dataset (ratings), where the course tags dataset includes data items such as course ID, teacher ID, grade ID, subject ID, difficulty, and time; the user ratings dataset includes data items such as student ID, course ID, ratings, and time.

4.3. Evaluation Metrics. Rating prediction indicator: Many websites have the function of letting users rate items such that this system also has this function; student users can rate the courses they study; if they get the user's rating of historical items, they can get a preference model to calculate the user's predicted rating of new items. The rating prediction metric is to evaluate the prediction result by calculating the accuracy or coverage rate of the predicted ratings. The coverage rate is the ratio of suggested things to total items in the system, and the higher the coverage rate, the more diversified the recommended products are, boosting the long-tail effect. In addition, there are two main indicators to

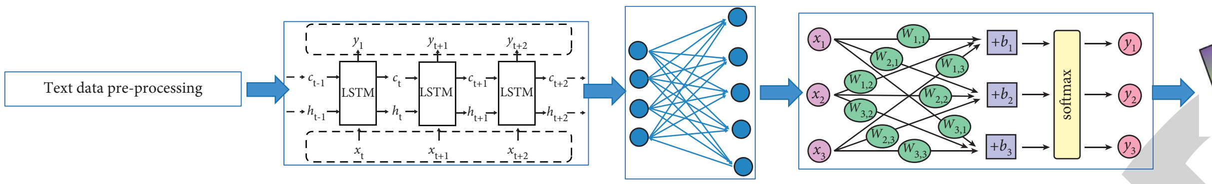

Figure 5: Text processing flow.

measure the accuracy, namely, Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE). MAE is the absolute formula shown in the following formula.

$$\mathrm{MAE} = \frac{\sum_{u,i\in T}\left|r_{ui} - p_{ui}\right|}{|S|}. \quad (6)$$

The RMSE is calculated as shown in the equation below.

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{u,j\in T}\left(r_{uj} - p_{uj}\right)^2}{|S|}}. \quad (7)$$

Evaluating the merit of the predicted item set can be used in the scenario of selecting Top-N item data for recommendation. Generally, websites make recommendations by listing the user's personalized predicted recommendation list, and this recommendation method is called Top-N recommendation. F-Measure is calculated by the following formula, where α is used to weight and reconcile the precision and recall rates.

$$F - \mathrm{Measure} = \frac{\left(\alpha^2 + 1\right) * \mathrm{Precision} * \mathrm{Recall}}{\alpha^2 * (\mathrm{Precision} + \mathrm{Recall})}. \quad (8)$$

We often set α in the F-Measure to 1; that is, the $F1$ value is calculated, and the value of $F1$ ranges from 0 to 1.

4.4. Experimental Results and Analysis. The traditional and upgraded models' prediction impacts are assessed through the study and comparison of experimental findings. Two sets of experiments are conducted in this section. Experiment 1 compares the rating prediction effects of different similarity models with different nearest-neighbor values, and Experiment 2 compares the recommendation accuracy, recall, and $F1$-values of different recommendation algorithms so as to analyze the recommendation effects of each recommendation algorithm.

The recommendation accuracy of different cosine similarity models is compared. Reducing the active user rating contribution and penalizing the time interval between users rating two courses are both optimizations of the traditional cosine similarity. We examine the classic cosine similarity (Sim), the cosine similarity that penalizes active users (Sim'-h), the cosine similarity that penalizes the rating time interval (Sim-f), and the cosine similarity that combines both types of penalties (Sim-m) (Sim-mix). This experiment uses four sets of K-values of 10, 20, 30, and 40, respectively, to examine the effect of the size of the number of nearest neighbors K on the system error values, and the RMSE values of different similarity models are provided in Table 2.

Table 2: RMSE for different similarity models.

Similarity model/neighborhood number K	10	20	30	40
Sim	1.143	1.113	1.091	1.105
Sim-h	1.125	1.084	1.032	1.042
Sim-f	1.123	1.078	1.035	1.057
Sim-mix	1.110	1.048	0.983	0.996

Table 3: Comparison of different recommendation algorithms.

	User-CF	Item-CF	CB	HybridR
Precision	0.548	0.635	0.623	0.804
Recall	0.493	0.572	0.561	0.724
$F1$	0.492	0.601	0.590	0.762

The change in RMSE values in the scenarios of different similarity models and different K values can be seen in Table 2. The root means a square error of the three improved similarity models is smaller than that of the traditional cosine similarity model in different nearest-neighbor cases, and the error optimization degree of Sim-h and Sim-f is not much different, while Sim-mix works best. (1) With K-values of 10 and 20, Sim-f works slightly better than Sim- due to the short time interval of user-rated items, and the penalty has less effect on the similarity h. (2) Conversely, for K-values of 30 and 40, Sim-h is more effective than Sim-f due to the selection of nearest neighbors, and the time interval of user-rated items is too long, resulting in an enhanced time penalty. (3) Sim-mix is derived from the combination of Sim-h and Sim-f, so it takes into account both the penalty for active users and the penalty for time, with minimal error and optimal effect. The four models do not work well when the nearest-neighbor K-value is 10 and work best when the root mean square error is minimized when the K-value is 30. Therefore, the Sim-mix model is optimal for similarity improvement at a K-value of 30. Recommended performance comparison. This experiment analyzes the recommendation effects of different recommendation models by comparing the Precision and Recall of four models: User-CF, Item-CF, Content-Based Recommendation (CB), and HybridR. The results of Precision, Recall, and $F1$-values of different recommendation algorithms are shown in Table 3 below.

The accuracy, recall, and $F1$-values of the collaborative user filtering are the lowest and the recommendation effect is poor; the item collaborative filtering and content-based recommendation algorithms are the second-best; the hybrid recommendation algorithm is better than the other three algorithms because it optimizes the cold start and long-tail by mixing Item-CF and CB weighting and improves the accuracy, recall, and $F1$-values.

5. Conclusion

In the new era, students' learning mindset has been very different from the past, and students' learning paths have been diversified. Traditional education should seize the opportunity to adapt to the information age's development, deepen the reform of the educational model, promote the exploration and improvement of online and offline integrated teaching, and strengthen the deep integration of information technology and education teaching in the new educational environment. In the postepidemic era, as long as a complete online and offline integrated teaching system is built based on information technology, teachers' ability to process and handle online resources, their ability to adapt to online teaching, and their awareness of online teaching are strengthened. To foster students' self-learning, hybrid teaching, which combines several teaching techniques and places students at the center of teaching, is used.

Data Availability

The datasets used during the current study are available from the author upon reasonable request.

Conflicts of Interest

The author declares that he has no conflicts of interest regarding the publication of this paper.

References

[1] G. Cai, Y. Fang, J. Wen, S. Mumtaz, Y. Song, and V. Frascolla, "Multi-carrier M-ary DCSK system with code index modulation: an efficient solution for chaotic communications," *IEEE Journal of Selected Topics in Signal Processing*, vol. 13, no. 6, pp. 1375–1386, 2019.

[2] K. Chandra, A. S. Marcano, S. Mumtaz, R. V. Prasad, and H. L. Christiansen, "Unveiling capacity gains in ultradense networks: using mm-wave NOMA," *IEEE Vehicular Technology Magazine*, vol. 13, no. 2, pp. 75–83, 2018.

[3] J. Du, C. Jiang, Z. Han, M. Shahid, and R. Yong, "Contract mechanism and performance analysis for data transaction in mobile social networks[J]," *IEEE Transactions on Network Science and Engineering*, vol. 6, no. 2, pp. 103–115, 2017.

[4] P. Paudel, "Online education: benefits, challenges and strategies during and after COVID-19 in higher education[J]," *International Journal on Studies in Education*, vol. 3, no. 2, pp. 70–85, 2021.

[5] W. Ali, "Online and remote learning in higher education institutes: a necessity in light of COVID-19 pandemic," *Higher Education Studies*, vol. 10, no. 3, pp. 16–25, 2020.

[6] L. Mishra, T. Gupta, and A. Shree, "Online teaching-learning in higher education during lockdown period of COVID-19 pandemic," *International Journal of Educational Research Open*, vol. 1, Article ID 100012, 2020.

[7] W. Bao, "COVID -19 and online teaching in higher education: a case study of Peking University," *Human Behavior and Emerging Technologies*, vol. 2, no. 2, pp. 113–115, 2020.

[8] P. F. J. García, A. Corell, G. V. Abella, and G. D. P. Mario, "Recommendations for mandatory online assessment in higher education during the COVID-19 pandemic," *Radical Solutions for Education in a Crisis Context*, pp. 85–98, Springer, Berlin, Germany, 2021.

[9] N. Almazova, E. Krylova, A. Rubtsova, and M. Odinokaya, "Challenges and opportunities for Russian higher education amid COVID-19: teachers' perspective," *Education Sciences*, vol. 10, no. 12, p. 368, 2020.

[10] R. N. Laili and M. Nashir, "Higher education students' perception on online learning during covid-19 pandemic," *Edukatif: Jurnal Ilmu Pendidikan*, vol. 3, no. 3, pp. 689–697, 2021.

[11] E. K. Agormedah, E. A. Henaku, D. M. K. Ayite, and A. A. Enoch, "Online learning in higher education during COVID-19 pandemic: a case of Ghana[J]," *Journal of Educational Technology and Online Learning*, vol. 3, no. 3, pp. 183–210, 2020.

[12] Y. M. Tang, P. C. Chen, K. M. Y. Law et al., "Comparative analysis of Student's live online learning readiness during the coronavirus (COVID-19) pandemic in the higher education sector," *Computers & Education*, vol. 168, Article ID 104211, 2021.

[13] M.-A. Maican and E. Cocoradă, "Online foreign language learning in higher education and its correlates during the COVID-19 pandemic," *Sustainability*, vol. 13, no. 2, p. 781, 2021.

[14] M. Rohman, D. A. S. Marji, and R. M. Sugandi, "Online learning in higher education during covid-19 pandemic: students' perceptions[J]," *Journal of Talent Development and Excellence*, vol. 12, no. 2s, pp. 3644–3651, 2020.

[15] C.-L. Chang and M. Fang, "E-Learning and online instructions of higher education during the 2019 novel coronavirus diseases (COVID-19) epidemic," *Journal of Physics: Conference Series*, vol. 1574, no. 1, Article ID 012166, 2020.

[16] M. Adnan and K. Anwar, "Online learning amid the COVID-19 pandemic: students' perspectives[J]," *Online Submission*, vol. 2, no. 1, pp. 45–51, 2020.

[17] M. Tesar, "Towards a post-covid-19 "new normality?": physical and social distancing, the move to online and higher education," *Policy Futures in Education*, vol. 18, no. 5, pp. 556–559, 2020.

[18] H. Jiang, A. Y. M. A. Islam, X. Gu, and J. M. Spector, "Online learning satisfaction in higher education during the COVID-19 pandemic: a regional comparison between Eastern and Western Chinese universities," *Education and Information Technologies*, vol. 26, no. 6, pp. 6747–6769, 2021.

[19] W. Striel kowski, "COVID-19 pandemic and the digital revolution in academia and higher education[J]," 2020, https://www.preprints.org/manuscript/202004.0290/v1.

[20] F. Zheng, N. A. Khan, and S. Hussain, "The COVID 19 pandemic and digital higher education: exploring the impact of proactive personality on social capital through internet self-efficacy and online interaction quality," *Children and Youth Services Review*, vol. 119, Article ID 105694, 2020.

[21] A. K. Arora and R. Srinivasan, "Impact of pandemic COVID-19 on the teaching - learning process: a study of higher

education teachers," *Prabandhan: Indian Journal of Management*, vol. 13, no. 4, pp. 43–56, 2020.

[22] M. K. Saraji, A. Mardani, M. Köppen, A. R. Mishra, and P. Rani, "An extended hesitant fuzzy set using SWARA-MULTIMOORA approach to adapt online education for the control of the pandemic spread of COVID-19 in higher education institutions," *Artificial Intelligence Review*, vol. 55, no. 1, pp. 181–206, 2022.

[23] O. Zawacki-Richter, "The current state and impact of Covid-19 on digital higher education in Germany," *Human Behavior and Emerging Technologies*, vol. 3, no. 1, pp. 218–226, 2021.