A study on student-oriented personalized diversified teaching model driven by artificial intelligence

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Abstract: This essay seeks to construct a varied teaching methodology and to support students' individualized growth. Collaborative filtering recommendation method is used to examine students' interests and pastimes by looking at the framework of intelligent recommendation system. The collaborative filtering algorithm, process of algorithm input, algorithm processing and algorithm output are analyzed in detail. According to the results, the customized teaching mode has a better advantage over the traditional teaching mode in terms of discussion time, classroom engagement, activity form, and learning content, which are correspondingly 20%, 19%, 40%, 30%, and 10% higher. 70% of the content in a course is process-based in the conventional teaching approach, which is more rigid, less flexible, and extensively structured. The personalized teaching mode, on the other hand, pays more attention to the flexibility of teaching, with a degree of flexibility of 60%.

1. Introduction

Education, as a practical activity of training people, is aimed not only at human development but also at the development of the country. However, if one model is used for lesson preparation, one method is used for lessons, one ruler is used for exams, and one standard is used for evaluation, this is not in line with the reality of students, and such instruction can only promote the growth of some pupils while inhibiting that of others [1-3]. Education is supposed to be equal, so that each person has a free and equal opportunity to develop his or her inherent characteristics. This requires that we follow the principles of individualism and develop the human personality. Adopting a personalized teaching model, to study to pay attention to the differences of students. In a school, in a class or even in a family, each person is different. Some are good at thinking, some are good at memorizing [4-6]. Some are independent and some are overly dependent. Individuals have special talents, and education should develop them according to their talents to make the most of them. Those who are good at thinking are guided to think in a way that makes them think more thoughtfully and logically. For those who are good at remembering, they should develop their ability to remember so that they will never forget. For those who are independent, let them learn on their own, at a pace that suits them, and the results will be good. Those who are dependent are given more attention and are constantly guided and supervised [7-10].

2. Collaborative filtering improvement algorithm based on intelligent recommendation

2.1 Intelligent Recommendation System

2.1.1 Collaborative filtering recommendation techniques

The four most common recommendation algorithms at the moment are content-based, collaborative filtering, association rule-based, and combination algorithms. In this study, we primarily employ the coordinated filtering recommendation algorithm to examine students' interests and pastimes and create a tailored multiple teaching model that is centered on them .Figure 1 displays the collaborative filtering algorithm's categorization.

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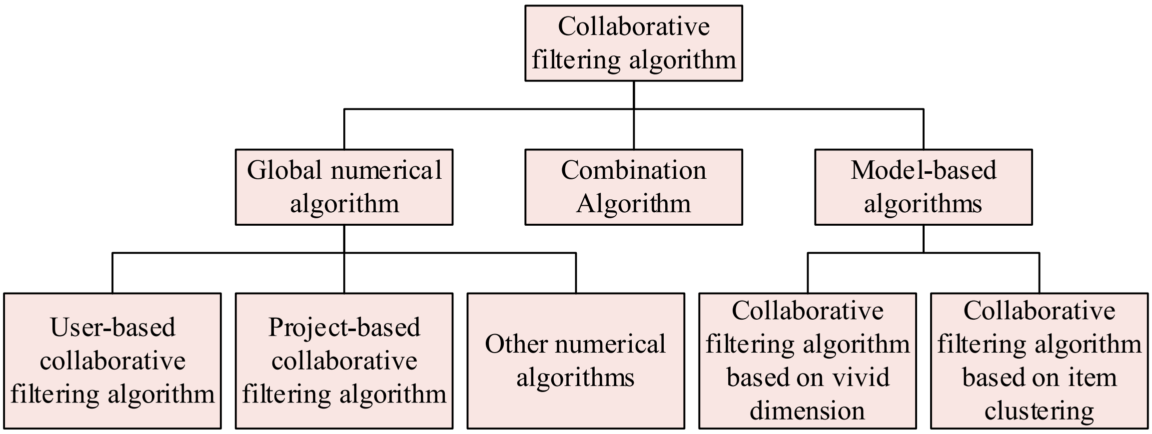

Figure 1 Collaborative filtering algorithm classification

2.1.2 Collaborative filtering recommendation algorithm workflow

It may also be succinctly stated as following three stages in order to understand a user item assessment data model as a whole: algorithm output, algorithm input, and algorithm processing.

2.2 User-based collaborative filtering recommendation algorithm

2.2.1 Data representation

The user-based collaborative filtering recommendation algorithm's core components are the user similarity metric, closest neighbor query, and anticipated ratings.

User-based collaborative filtering suggestions need the creation of recommendations based on data regarding the item ratings given by various users.

2.2.2 Nearest Neighbor Queries

The users with comparable rating or purchase patterns to the present user are referred to as nearest neighbors. The User-based Collaborative Filtering Recommendation Algorithm's closest neighbor query phase is essentially the model construction phase. The following steps are taken to determine how similar users i and j are to one another: first, all products that users i and j have rated are acquired; next, the similarity between users i and j is determined using various similarity measures; and finally, the result is designated as $sim(i, j)$.

Correlation similarity

Let I_{ij} represent the collection of things that users i and j rated together. The Pearson correlation coefficient equation (1) calculates the similarity $sim(i, j)$ between users i and j:

$$sim(i,j) = \frac{\sum_{c \in Iij}\left(R_{c,i} - \overline{R}_i\right)\left(R_{c,j} - \overline{R}_j\right)}{\sqrt{\sum_{c \in Iij}\left(R_{c,i} - \overline{R}_i\right)^2}\sqrt{\sum_{c \in Iij}\left(R_{c,j} - \overline{R}_j\right)^2}} \tag{1}$$

$R_{c,i}$ indicates the rating of item i by user c, $R_{c,j}$ indicates the rating of item j by user c, and $\overline{R}_i$ and $\overline{R}_j$ may indicate the average rating of items i and j, respectively.

2.2.3 Recommendation generation

The similarity metric mentioned above is used to find the target user's closest neighbors, after which the appropriate suggestions are generated. Let NN_u serve as a representation of the user u's collection of closest neighbors.

3. Accuracy analysis of student-oriented recommendations

3.1 Final prediction based on user learning direction clustering

Meanwhile, the similarity between users is determined using the enhanced similarity calculation approach based on user attributes in order to decrease the discovering space of nearby individuals and increase prediction accuracy, and then the users are classified using this improved collaborative algorithm so that all users are classified into K cluster $C_1, C_2, \cdots C_k$, where $C_1 \cup C_2 \cup \cdots \cup C_k = C$, and $C_i \cap C_j = \varnothing, i, j \in [1, k]$. Then, for $u, v \in C_k, k \in [1, K]$, then, according to the dense user learning content rating matrix obtained in the previous stage FR, users u and v have evaluated the learning content and set $S_{uv} = A_u \cup A_v$, then the other users v in C_k are neighbors with similar interests in u, and then by calculating the similarity $sim(u,v)$ between the target user u and the neighbor v users in the cluster in which it is located, the K users with the greatest similarity are selected as the nearest neighbor set $KNN(u)$ of the target user

After making the final forecast, the values are sorted from highest to lowest in descending order, and the top N items are selected to be recommended to u, i.e., the Top-N item recommendation set is generated.

3.2 Recommendation algorithm evaluation criteria

Before a recommendation system is used, it is very important to evaluate both the recommendation algorithm and the system. In order to improve the upcoming work, the assessment can quickly indicate the suggestion quality of a recommendation system. Common evaluation criteria include accuracy, coverage, diversity, novelty, and surprise.

4. Analysis of the collaborative filtering algorithm-based individualized multiple teaching paradigm

4.1 Analysis of Individualized Multiple Teaching Model

In order to confirm that the personalized teaching model may operate and be used under the intelligent recommendation collaborative algorithm, the practice was carried out in the introductory course of educational technology by comparing it with the traditional teaching model. The study was conducted with unit teaching as a stage, and each stage of teaching was followed by analysis of online learning behavior and evaluation of online teaching, so as to guide learning and adjust the next stage of teaching in a targeted manner.

Before the course began, the analysis was focused on five aspects: network usage, awareness of network learning, learning habits, general learning characteristics, and professional pre-awareness.

(1) Internet usage

The first three contents are about the analysis of students' internet usage, and the results are shown in Table 1. Students are not unfamiliar with the Internet, and most of them have a reasonable number of hours of Internet access every day. Not many students in the whole class go online for learning purposes, and educators must focus on helping kids use the Internet for learning.

Table 1 Students' Internet use

title	Options and percentages			
The online age of students	1 year	1-3 years	3-5 years	More than 5 years
Online time per day	1 hour	1-3 hours	3-5 hours	More than 5 hours
Main purpose of surfing the Internet	Follow current events (14%)	Study (40%)	Make friends (26%)	Life and entertainment (20%)

(2) Awareness of personalized learning

Students' attitudes toward the personalized pluralistic learning model are shown in Table 2. For this form of personalized learning, 65.3% of students said they were somewhat interested, 4% said they were not interested but willing to accept it, and 30.7% said they were very interested.

Table 2 Student attitude statistics

Attitudes towards personalized learning	Have some interest in	Not interested in	Very interested in
Number of students	32	2	15
proportion	65.3%	4%	15%

When comparing the student-oriented diversified teaching mode to the traditional teaching mode, the overwhelming majority of students believe that the high acceptance and richness of learning contents, the ability to communicate and fully communicate with teachers and classmates in time, and the very novel and interesting design of learning activities are the modes' greatest advantages. Figure 2 displays the partial percentages for the two instructional approaches. The customized teaching mode offers a better advantage over the conventional teaching mode in terms of discussion time, classroom engagement, activity form, and learning content, which are correspondingly 20%, 19%, 40%, 30%, and 10% higher. In the traditional teaching mode, teaching is more rigid, less flexible and heavily formatted, with 70% of the content in a course following the process. The personalized teaching mode, on the other hand, pays more attention to the flexibility of teaching, with a degree of flexibility of 60%.

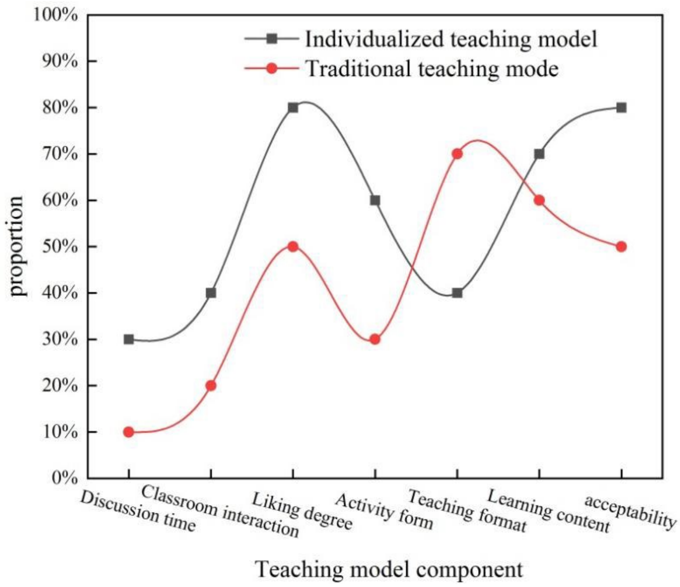

Figure 2 Proportion of partial teaching mode

(3) Personalized learning habits

The survey of whether students need teachers in personalized learning is shown in Table 3. Among the 49 students' data collected, 31% of the students thought that teachers were necessary in personalized learning, 66% thought that teachers were still needed in personalized learning, and 3% thought that teachers were dispensable.

Table 3 Whether personality learning needs a teacher

Whether teachers are needed for personalized learning	need	Occasionally needed	Not much need
Number of students	13	30	6
proportion	26.8	61.2	12

(4) General learning characteristics

Regarding the level of students' learning ability as shown in Figure 3, for the ability of mastering knowledge, 30% of the class considered their ability level of mastering knowledge to be A, 40% considered their ability level of mastering knowledge to be B, and 15% considered their ability in mastering knowledge to be C. 40% of the students had weak knowledge innovation ability, and 23% of the students had good knowledge 63% of the students have good learning practice ability.

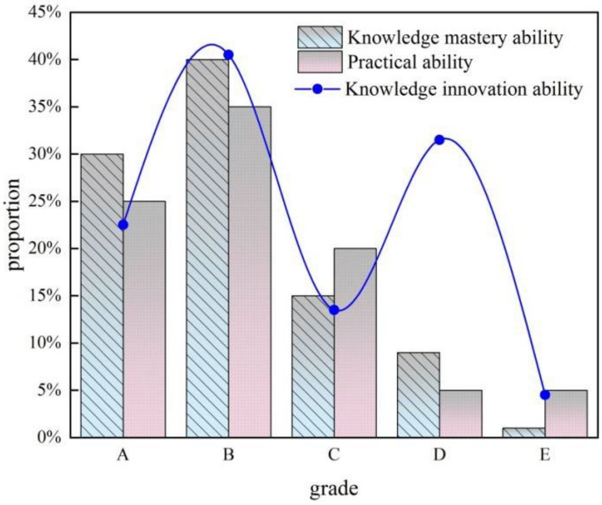

Figure 3 The proportion of students' learning ability level

5. Conclusion

This study builds a student-led individualized multiple teaching model using the collaborative filtering algorithm from the intelligent recommendation system to statistically examine students' learning interests and pastimes. The main findings are as follows:

(1) The application of artificial intelligence helps pupils become more creative. 14% of students use the internet primarily to learn about practical topics, while 40% of students use it to study. The individualized teaching method can increase students' capacity for knowledge mastery and innovation compared to the conventional teaching method. 63% of students have better learning practice ability and 60% have better knowledge innovation ability.

(2) Using collaborative filtering algorithms to classify students' preferred teaching contents and teaching methods. For this form of personalized learning, 65.3% of the students expressed some interest, 4% of the students expressed no interest but were willing to accept it, and 30.7% of the students expressed great interest. During the teaching process, the information of students' participation in various activities will eventually be aggregated to the teacher's end. Teachers can use the data to accurately understand students' participation and thus better develop teaching programs.

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