Analysis of learner group characteristics and intervention strategies in virtual learning communities under the xAPI standard

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Abstract. At present, there are problems such as low learning efficiency and poor learning effect of learners in the field of virtual learning communities. How to accurately analyze the learning characteristics of learner groups in virtual learning communities and provide differentiated learning enhancement strategies for learners has become a hot spot in the current research on virtual learning communities. This paper introduces the emerging xAPI standard in the field of data collection and storage, and proposes a model for analyzing the learning characteristics of learner groups applied to virtual learning communities based on previous research, and conducts specific experiments based on this model to cluster the learner groups in virtual learning communities and analyze them from multiple perspectives with different learning characteristics. We propose differentiated intervention strategies in order to provide suggestions for the relevant teaching staff and provide a better basis for the development of virtual learning community education.

Keywords: virtual learning communities; learner behavior analysis; xAPI;

1 Introduction

In order to respond to the national call to solve the problems of poor academic monitoring mechanism and low learning efficiency in the field of online education.[1] In this study, we try to introduce the interface specification xAPI proposed by the ADL project, which is based on the SCORM standard, to collect and store the learner data obtained from the virtual learning community. [2] At the same time, based on the previous research, the author constructs a learner group learning behavior analysis model, which describes the learning behavior of each learner in the learning community through the current common learning record system, such as the number of learning resources posted, online questions, answers to questions, favorite posts, downloading learning materials, etc., to cluster and analyze learners with different learning characteristics, and then propose targeted intervention strategies for the learners with different characteristics. This study is intended to provide a powerful contribution to the sustainable and effective development of online education in the post-epidemic era.

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2 Relevant literature studies

In order to improve the research learning experience of secondary school students, Yu Minghua of Shanghai Normal University adopted an xAPI-based multi-source data fusion method on the basis of combing existing methods of multi-source data fusion, and used a data-level fusion method to build a research learning multi-source data fusion architecture based on the xAPI specification to develop a learning behavior record library.[3] Huixiao Qiao from East China Normal University proposed an open learning analysis architecture based on xAPI and an open learner behavior analysis model by semantic decomposition of open learners' learning behaviors. [4] And Fang Haiguang and Chen Junda from Capital Normal University start from the perspective of learning data, use the xAPI specification standard as the basis for data-based analysis of digital learning resource interaction design, and complete the design of interactive resources based on standard data on the basis of this research.[5] Tang Yewei and Zhao Tong from Northeast Normal University discuss the origin, characteristics and working principles of xAPI, and analyze the differences between SCORM and xAPI standards, introduce typical cases developed using xAPI and propose its core elements to support smart learning.[6]

3 Theoretical and technical support

The humanistic theory in education is a necessary theoretical basis for the process of informatization in education. This theory emphasizes the respect of education for the natural character and dignity of the learner. [7] The xAPI (also known as the Experience API) used in this study is a widely used learning technology specification that has the advantage of being a powerful learning profile recorder that can capture learner learning process data in a cross-platform manner, and supports the use of multiple programming languages to store the data in a consistent format. In the virtual learning community designed in this study, students' activities are recorded through xAPI and stored in the Learning Record Storage System (LRS) in a consistent format, which includes information about learners' learning process and learning outcomes, which is important for learner activity analysis and learning characteristics classification. The learning experiences of students under the standard are tracked and recorded by the Learning Record Provider (LRP), and the records are recorded through the Learning Record System (LRS), and eventually the various learning experience data are provided to the researcher, i.e., the Learning Record Consumer (LRC), as shown in Fig. 1.

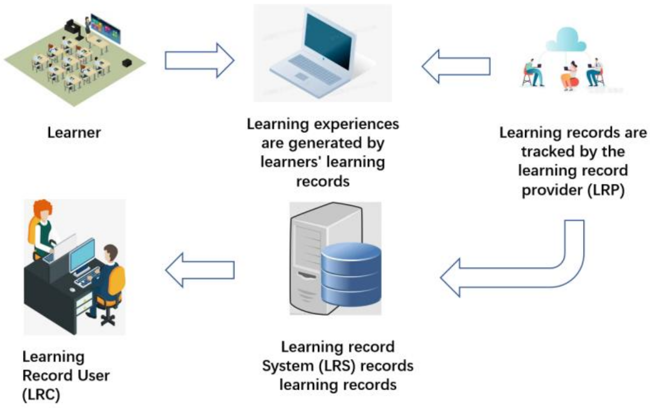

Fig.1. Flow chart of learner learning experience tracking under xAPI standard

4 Group portrait model construction

4.1 xAPI standard under Virtual Learning Community Group Portrait Model Architecture Design

The learner group portrait model established in this study uses the virtual learning community platform as the experimental data collection platform to collect and store basic information and learning process data of learners. Since the designed platform is based on the xAPI standard for data collection, all data will be processed in a uniform format and stored in the LRS (Learning Record System). The basic information of students (gender, student number, class, etc.) and learning process data (learning hours, number of questions collected and answered, number of discussions, etc.) can be obtained by exporting the database data. Once these key data are obtained, they can be clustered and analyzed to form a picture of multiple categories of learning groups with different learning styles, characteristics, and preferences. This group segmentation can provide a reference basis for educators and an important guarantee for teaching researchers to maintain the quality of online education in the post-epidemic era. The architecture design of the learner group portrait model used in this study is shown in Fig. 2.

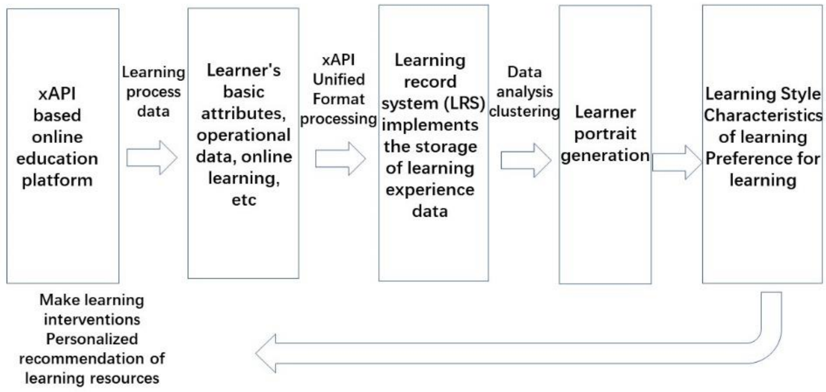

Fig.2. Architecture design of learner group portrait model under xAPI standard

4.2 Case experiment process

The purpose of this case study is to collect data on students' behavioral attributes on the virtual learning community platform (including the number of learning resources shared, the number of questions left, the number of questions answered, and the average scores obtained on quizzes) through the xAPI standard to conduct a cluster analysis of learners and to analyze the relationship between the results achieved by learners (characterized by the average scores obtained on quizzes) and various influencing factors. In this experiment, 121 students from a higher vocational college in Shandong province participated in the virtual learning community, and the experiment was completed within five weeks. Students can browse and download learning resources (including PowerPoint, source programs, etc.) from the download module of the learning resources post. Through the platform, teachers can post quizzes to analyze the students' learning situation and count the average scores, which can directly characterize the grades obtained by the students.

Since the learning record system LRS is essentially a database, the records stored in the LRS database can provide accurate and reliable data for this experiment. After the experiment was completed, a total of 121 test students' valid records were obtained, and the author selected the database records with four attributes: the number of learning resources shared, the number of questions left, the number of questions answered, and the average scores obtained from knowledge tests to conduct data clustering analysis, so as to explore the learning characteristics of different groups of learners, and then propose learning intervention strategies with different characteristics for different groups of learners, so as to help teachers and other educational administrators improve teaching quality and management efficiency. It helps teachers and other educational administrators to improve teaching quality and management efficiency.

5 Data analysis process

5.1 Determining the optimal number of clusters using the elbow method

In this study, the elbow method was used to determine the optimal number of clusters. As the number of clusters increases during clustering, the degree of aggregation of each cluster gradually increases, so its SSE (sum of squared intra-cluster errors) value will gradually decrease.[8] When the number of clusters is close to the true number of clusters, the SSE decreases abruptly and then tends to level off gradually, and the whole relationship graph resembles the shape of an elbow. The relationship between SSE and the number of clusters i generated according to the elbow method is shown in Fig. 3. From the figure, it can be seen that before the value of i is less than 3, the SSE value decreases more, and the image shows an obvious inflection point at the value equal to 3. After the value is greater than 3, the decreasing trend of SSE value tends to level off, which shows that the optimal number of clusters should be 3 classes.

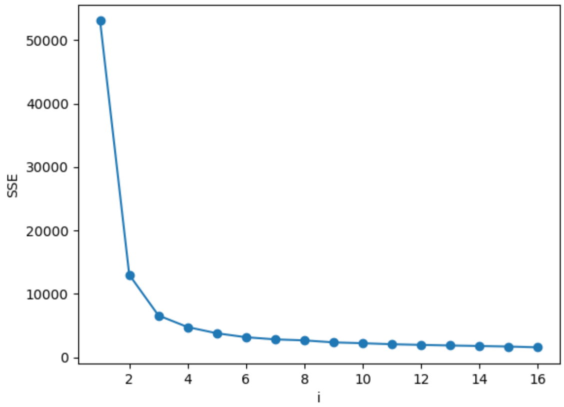

Fig.3. Graph of elbow method to determine the optimal number of clusters

5.2 Clustering using FCM algorithm

Before performing this clustering, the author first standardizes each column of data, and since the algorithm uses the strategy of initializing the affiliation matrix, calculating the cluster center, and then updating the affiliation matrix after calculating the number of cost rows, the basic algorithmic idea is to make the maximum similarity between objects classified into the same cluster and the minimum similarity between different clusters. The basic idea of the algorithm is to maximize the similarity between objects classified into the same cluster and minimize the similarity between different clusters. The implementation of the program requires first initializing the affiliation matrix with a random number between 0 and 1, then calculating the c cluster centers Ci (where i=1,...,c), and then calculating the value function.[9] If it is less than some determined value or its change value relative to the last value of the value function is less than some threshold value, the algorithm stops, otherwise it updates to compute a new affiliation matrix and recalculates the clustering centers. Most scholars currently use K-means clustering method when performing clustering analysis of learner behavior characteristics, and to avoid errors due to clustering methods, this study uses FCM clustering algorithm to analyze the results after the experiment as shown in Fig.4.

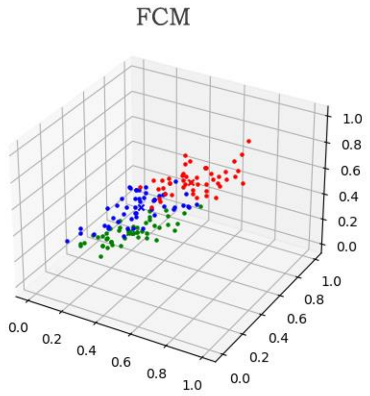

Fig.4. Cluster analysis results of FCM algorithm

5.3 Interpreting learner group characteristics

The clustering results shown above were obtained by the FCM clustering algorithm, and the three groups of learners have their own unique learning characteristics. The first group of learners is tentatively named Highly Engaged Active Learners, with a total of 45 learners, accounting for 37.2% of the total sample, and this group of learners has posted the most resource sharing posts, with an average of 49.1 times, and has the best participation among the three groups of learners. The average number of questions left in the comments reached 34.7, the average number of questions answered reached 59.4, and the average score of passing the knowledge quiz was 80.2. They are characterized by their active online learning behavior, their ability to play a leading role in the virtual learning community, their high participation in knowledge sharing and discussion, their positive attitude and good learning outcomes.

The second group of learners is tentatively named as moderately active learners, with a total of 36 people, accounting for 29.8% of the total sample. The average number of times these learners posted learning resources was 41.7, the average number of times they left questions was 32.3, the average number of times they answered questions was 46.1, and the average score of the quiz was about 73.0. These learners are more active in participating in the virtual learning community, have better learning completion and positive learning attitudes, and are important targets for improvement in the virtual learning community, and can achieve relatively good grades through the interaction and sharing effects in the virtual learning community.

The third group of learners, tentatively named, has a low participation level and is relatively negative. has a total of about 40 learners, accounting for 33.1% of the total sample, and the average number of times this group of learners posts learning resources is 33.2, which is a lower willingness to share knowledge among the three groups. The main reason for this is that this group of learners usually asks questions to meet the requirements of teachers, to pass course exams or to improve their grades. However, the frequency and number of questions answered are significantly lower than those of the above two categories, with an average of 18.6 questions answered. The average score of this group of learners in the knowledge test is also the lowest among the three groups, with an average score of 66.5. It can be concluded that this group of learners has a low willingness to share and interact with knowledge, and therefore the learning effect is relatively poor.

6 Strategies for differentiated learning interventions for groups of learners in virtual learning communities

The first category of learners belongs to the more active learning group because of their higher participation and better learning results. To protect students' privacy and other students' self-esteem, we can adopt relatively mild messages such as "Congratulations to so-and-so for winning the title of resource sharing king in this learning community", "So far, so-and-so has answered the most questions correctly, please study actively", etc. This kind of encouragement helps such learners to have a higher sense of acquisition and recognition of the content they are currently learning, so that they can carry out subsequent education and teaching. The enhancement strategy can be achieved through the promotion of high quality learning resources, and teachers can provide more in-depth learning resources to these learners to achieve differentiated instruction.

The second group of learners has a moderate level of participation and has achieved certain learning outcomes but is poorer than the first group of learners. The author believes that for this group of learners, a unified approach of affirmation and reinforcement should be used for learning interventions. Teachers can re-promote the learning resources that these learners have not mastered, and send messages such as "Current academic achievement is at a good level, actively sharing learning resources and posting knowledge to improve your ranking, please keep up the good work" in the personal message module. The affirmation of learners' achievements can effectively stimulate their enthusiasm for learning, so that they can effectively complete the content taught by the teacher in the formal course and achieve the effect of re-enforcement of learning results.

The third group of learners has a lower level of participation in learning, and is lower than the first two groups of learners in terms of sharing resources, answering questions, and obtaining learning results, and is a relatively negative group of learners. Teachers can communicate with learners in private to understand the deep-seated reasons why learners fail to complete the learning seminars on time, admonish learners who deliberately brush up on the number of questions to improve their ranking, and arrange academic support groups to help students who have real difficulties in learning, while teachers can also push basic learning resources and exercises for such learners to help them replenish their foundation. Through such a hierarchical approach, learners who are relatively weak can keep up with the pace of the learning community and improve their academic performance by correcting their learning attitudes.

7 Conclusions

In the context of the post-epidemic era, the time spent by the majority of learners applying virtual learning communities as educational scenarios for learning and seminars will increase substantially.[10] This study collects learning record data through virtual learning communities conforming to the new xAPI standard, and completes the cluster analysis of learner groups and the characteristic analysis of three types of learner groups using the FCM algorithm. Finally, the authors propose detailed differentiated intervention strategies for the different three types of learner groups in order to provide educators with a theoretical basis to support the construction and teaching of virtual learning communities. At the same time, this study can further improve and enhance the data collection and analysis process, and better provide assistance for education informatization reform.

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