Research on Online Learning Behavior Intervention Mechanism Based on Intelligent Technology

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Abstract. This study analyzed the learning behavior data of online learners in Open University, and classified their learning behavior into four categories: high participation, relatively high participation, moderate participation and low participation. The study proposed interventions for learning behavior, such as early warning of academic performance, matching suitable teaching strategies, and providing adaptive push services.

Keywords: online learning · learning behaviors · Data analysis · Intervention mechanisms

1 Introduction

Learning analytics techniques emphasize data-based learning description, diagnosis, prediction, and intervention [1]. This study analyzes the learning behavior of lifelong education learners in Open University, performs data mining and analysis on learners' online learning behavior, and summarizes the learning prediction and feedback mechanisms of different types of learners based on education teaching theory. We will focus on the following two questions: First, what are the types of learners? Second, how to motivate learning behaviors for different types of learning groups to achieve adaptive learning?

2 Research Objects

This study is planned to take the course "Fundamentals of Computer Application" as an example. This course is a compulsory general education course for undergraduate majors, with a learning duration of 12 weeks. The learning method is mainly online learning, and students need to complete the corresponding learning activities according to the requirements of weekly learning objectives.

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Table 1. The demographic characteristics of students

Specialized subject	gender	Age group						Total
		21–25	26–30	31–35	36–40	41–45	46–50	
Performance (6 persons)	male	4	0	0	0	0	0	4
	female	1	1	0	0	0	0	2
Engineering Management (24 persons)	male	2	6	7	5	0	1	21
	female	0	0	1	1	1	0	3
Business Administration (118 people)	male	13	11	22	11	6	2	65
	female	14	7	18	8	6	0	53
Software (7 persons)	male	0	2	0	2	0	0	4
	female	0	1	1	0	1	0	3
Total (proportional)	—	34 (21.9%)	28 (18.1%)	49 (31.6%)	27 (17.4%)	14 (9.0%)	3 (1.9%)	155

3 Analysis of Learners' Characteristics

There are 155 students in this research course. Analysis of the demographic characteristics of students (shown in Table 1) shows that the age range of students is between 21 and 48 years old, and most students are 31–35 years old. From the perspective of student gender, male students account for 60.6%, while female students account for 39.4%. The average age of both male and female students is 32 years old.

The main characteristics of learners of this course are: (1) being older than ordinary college students, and (2) having certain industry experience. Students' majors are generally related to the industry they are engaged in, and they have some practical experience. (3) information literacy is relatively high. Students are concentrated in the age of 25–40, have experience in using Internet, and their information literacy can meet the needs of online learning. (4) High working pressure. Most students engage in distance learning after work, and there is a common phenomenon of high work pressure and insufficient learning time.

4 Data Collection

In this study, Excel was used to conduct preliminary collation and statistical analysis of the data exported by the Moodle learning platform. Learning behavior refers to the behavior of learners when participating in online learning, including the number of visits to courses, the length of online learning, the degree of completion of video viewing, the completion of online homework, discussion and communication, and academic performance [2].

5 Learning Behavior Data Analysis

This study analyzes the learning behavior of 155 students in the course of "Fundamentals of Computer Application". All students are divided into seven learning groups, each of which is equipped with a tutor and a class adviser. During the entire learning process, the tutor needs to respond and review the students' posts, assignments, and other content within the specified time, guiding students to conduct online learning, and the class adviser needs to remind students to complete various learning tasks on time and as required.

5.1 Data Collection and Cleaning

This study obtained a total of 78891 pieces of learning behavior data and student learning effectiveness records, including data on students' participation in learning the course content, accessing various teaching resources, answering discussion area questions, submitting assignments, participating in tests, and grades, as well as responses from various role teachers to student behavior. After further classifying and cleaning the initial data, 5155 unrelated data were removed, and duplicate data were removed. Finally, 36287 valid data were obtained.

5.2 Analysis of Access Times of Course Resources

A. **Analysis of the overall number of resource visits.**

Based on the analysis of 155 students' course access data (collectively referred to as "resource access times"), it was found that the highest number of access record data was 597, and the lowest number was 2. Students with higher access record data have a relatively high degree of participation in learning, while students with lower access record data have a lower degree of participation in learning.

Through a segmented analysis of the total number of times students visited curriculum resources, it was found that the total number of times most students visited curriculum resources ranged from 106 to 306.

B. **Analysis of Average Visits to The matic Resources.**

The learning schedule for this course is to complete a topic every two weeks. Based on the statistical analysis of the number of visits to different topics by learners, the average number of visits to each topic during the 12 week learning process for six topics is shown in the figure. In Fig. 1, the ordinate represents the average number of visits, and the abscissa represents the unit topic of learning. The solid line represents the number of times students actually visit the platform or resources, and the dotted line represents the trend in the number of visits. Overall, the average number of visits to each topic of the course is 18.27, and the learning cycle for each topic is 14 days, with an average of 1.31 visits per day. On the whole, there is a phenomenon of students' online learning that the number of visits decreases and their enthusiasm for learning decreases over time.

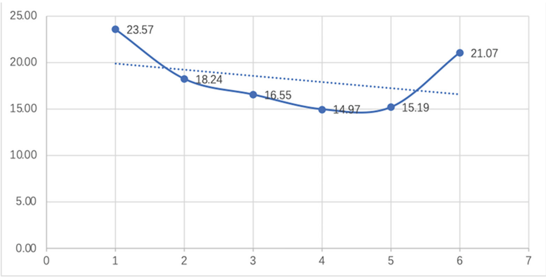

Fig. 1. Average Visits to The matic Resources

5.3 (3) Analysis of Video Resources Access

The learning resources for this course are mainly videos, with a total of 83 video resources. According to statistics, 61 videos were actually visited and viewed, while 22 videos were not visited. The content analysis of 22 video resources that have not been accessed is mainly focused on content related to basic operations in the three topics of "Word Text Editing", "PowerPoint for Presentation", and "Computer Network". This is related to the fact that students have mastered the basic operations of Word, PowerPoint, and computer networks in their daily work, and other in-depth video resources have been accessed. It shows that the use of learning resources by on-the-job students has the characteristics of selective on-demand learning.

Researchers further explore the specific access situation of course video resources and analyze the viewing progress of video resources. The total length of all video resources in this lesson is 1272 min, with an average video resource duration of 16.96 min, a minimum video duration of 2.47 min, and a maximum video duration of 42.77 min. 61 resources were visited, with a total number of visits of 312 and a total number of visits of 50, which means that one-third of the students actually viewed the course video resources. The viewing progress of 312 video accesses was analyzed, and the viewing progress was divided into five levels, ranging from 1 to 5, based on a range of 25%, 50%, 75%, 99%, and 100%. The specific statistics are shown in the table below (Table 2). The data in the table shows that 30.77% (level 5) of video resources were completely viewed, 69.23% (level 1–4) of video resource learners gave up watching during the process, and 38.14% (level 1) of video resource learners gave up watching before finishing a quarter.

Table 2. The analysis of video accesses

level	Watch the progress zone	Visits	percentage	Cumulative percentage
1	0%–25%	119	38.14%	38.14%
2	25.1%–50%	46	14.74%	52.88%
3	50.1%–75%	29	9.29%	62.18%
4	75.1%–99%	22	7.05%	69.23%
5	99.1%–100%	96	30.77%	100%

Table 3. The analysis of video viewed time

Duration of the visit	Visits	percentage	Cumulative percentage
0–5 min	144	66.67%	66.67%
5.1–10 min	34	15.74%	82.41%
10.1–15 min	23	10.65%	93.06%
15.1–20 min	10	4.63%	97.69%
More than 20 min	5	2.31%	100%

The researchers continued to analyze the length of time spent accessing 216 incomplete video resources at levels 1 ~ 4, and found that 66.67% of learners gave up learning video resources within less than 5 min. 15.74% of learners choose to give up within 5–10 min (show in Table 3).

Based on the above analysis, there is a polarization phenomenon between students who give up watching before 25% of the video playback progress and students who complete the video viewing entirely, indicating that there is a significant difference in students' participation and initiative in learning. Some students are slack in learning video resources, lack enthusiasm for learning, and lack self-control [3]. From the analysis of interview duration, it is important to present and explain the content of the first 5 min of video in online learning, which becomes a key point to attract learners to continue to complete video learning. Long video explanations can easily lead to learners' fatigue and inattention, leading to giving up watching.

5.4 Analysis of Interaction and Communication

The course includes interactive activities such as discussion areas and questionnaires, which are divided into optional content that does not record scores and mandatory content that records scores. Statistical analysis of the text information posted by students shows that students' participation in the communication and interaction of selected content parts is relatively low, with an average participation of 15.0%. For the communication and interaction of required content parts, their participation is relatively high, with an average participation of 84.9%. For discussion topics with high student participation, many learners in the replies have personalized thoughts and personal opinions on the discussion topic, and mainly respond to topic posts. There are fewer debates, opinion collisions, and in-depth communication interactions between students and students around a certain topic. To some extent, it indicates that students can actively participate in learning tasks, but their awareness of active questioning is not strong, and the depth of participation needs further guidance.

5.5 Analysis of Assessment Task Participation

The assessment method of the course is a combination of formative assessment and summative assessment, each accounting for 50% of the total score. The formative assessment is based on completing corresponding assignments and exams on a weekly basis, while the final assessment is based on completing a set of comprehensive examination papers after the course ends, with a duration of 1 h.

A. **Analysis of the completion of formative assessment tasks.**

The formative assessment of the course mainly adopts assignments and tests, mainly in the form of practical training tasks, case studies, and test questions to comprehensively assess students' abilities. Some of the assessment content is difficult and the types of questions are diverse. Students need to complete and submit online according to the time requirements. A total of 13 formative assessment tasks have been set up in the course, with 35.48% of students completing all of them, 81.94% of students completing more than 10 assessment tasks, and 94.19% of students completing more than half of the assessment tasks. The performance of formative assessment tasks accounts for 50% of the total course performance, and the average formative assessment score of students is 77.87 points.

B. **Analysis of the completion of final assessment tasks.**

The final assessment of the course is completed through an online quiz that covers knowledge points on all topics of the course. Students have two opportunities to answer questions, each time for 60 min, and their scores are recorded based on the highest score of the two answers. 83.2% of the students completed the final test, with an average score of 90.57. Among them, 91 students scored above 90 points, 19 students scored between 80 and 89 points, 11 students scored between 70 and 79 points, 6 students scored between 60 and 69 points, and 2 students failed. 16.8% of students did not participate in the final exam, with a score of 0. The average final exam score for all students was 75.38 points.

From the analysis of the relationship between the completion of formative and summative assessment tasks and performance scores, students' learning participation is characterized by task driven and performance driven characteristics. Students with scored assignments and tests have a high degree of participation, while students with non scored other activities have a low degree of participation, with a large gap between the two. The students with high scores in the final assessment have a high degree of participation.

5.6 Analysis of Academic Performance

A. **Analysis of the distribution of learning achievements.**

According to comprehensive statistics, among 155 students, the number of people who failed was 28, accounting for 18.1%, the number of people in the 60–69 score range was 7, the number of people in the 70–79 score range was 16, accounting for 10.3%, the number of people in the 80–89 score range was 33, accounting for 21.3%, and the number of people in the 90–100 score range was 71, accounting for 45.8%. The overall score distribution is basically inverted U-shaped, and the score distribution is not ideal (show in Fig. 2).

B. **Correlation analysis of Learning performance and students' learning behavior data.**

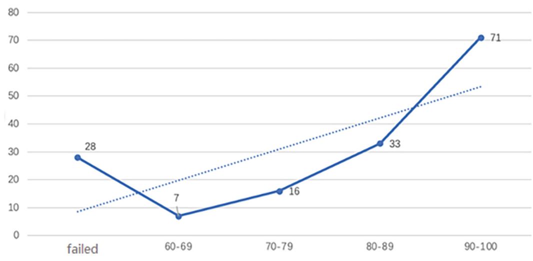

Fig. 2. Analysis of the distribution of learning achievements

Table 4. The correlation coefficient between learning performance and learning behavior data

	The number of times the resource was accessed	the length of video was watched	Interact with each other		Assess task participation	
			Select as content	Must-do content	Formative assessment	Finality assessment
Academic performance	0.4329	−0.0195	0.1927	0.8284	0.8435	0.9593
correlation	medium	weak	Weaker	strong	strong	strong

Through the relationship between academic performance and the number of visits to course resources, video visits, interactive communication, and the completion of assessment tasks. The correlation coefficient is calculated using the correlation coefficient data analysis tool in Excel software (show in Table 4). The closer the value is to 1, the stronger the correlation is. The closer the value is to 0, the weaker the correlation is. The analysis shows that the correlation between students' academic performance and the number of resource visits is general, while the correlation with video visits and the interactive communication content of the optional part is not significant, while the correlation with the mandatory part of the interactive communication content and the participation in the assessment task is significant [4].

Overall, students with high scores will also have relatively high learning participation, and the lower the score, the lower the participation.

6 Classification of Learning Behavior Characteristics of Learners

By analyzing the online learning behavior, we classified the learners into four categories according to their participation, they were high participation type, relatively high participation type, moderate participation type, and low participation type.

High participation type learners have a higher degree of active participation in learning under the network environment, they have a higher degree of adherence to the course learning platform, and have a higher enthusiasm for using the network for learning, they also have a higher degree of participation, they are willing to cooperate in learning, have a strong self-regulation ability, and are good at using scattered time for fragmented learning.

Relatively high participation type learners have a high degree of participation in online learning, and a high degree of adherence to the course learning platform, they got a good learning effect [5]. Individual learners tend to adopt a reflective approach to observing and processing information.

Moderately engaged learners have moderate participation in online learning, moderate adherence to the course learning platform, and moderate self-consciousness. Their motivation for learning is mainly to complete learning tasks, so almost all types of learning behaviors are moderate, with average learning outcomes.

Low participation learners have low participation in online learning, low adherence to the course learning platform, poor motivation, and poor self-regulation ability. They need external supervision and control to complete learning tasks. The purpose of participating in learning is only to complete learning tasks, and their learning effect is poor.

7 Strategies and Suggestions for Intervention Mechanisms of Learning Behavioral

Firstly, academic early warning should be conducted according to the behavioral rules of different types of learners. Firstly, academic early warning and intervention should be given according to the learning participation status [6]. Secondly, academic early warning and intervention are given based on predicted learning outcomes.

Secondly, determine teaching strategies based on the behavioral rules of different types of learners. The results of learning behavior data analysis can enable teachers to timely understand the characteristics, facilitate teaching in accordance with their aptitude, determine teaching strategies and improve teaching resources, and provide guidance and intervention for learners' effective learning [7].

Thirdly, adaptive push services are implemented based on the behavioral rules of different types of learners. Build a resource push service mechanism and create an adaptive learning system. Emphasize resource push with learning space as the core, and send appropriate resources required by different learners into personal learning spaces [8]. According to the results of data mining, personalized learning push services are provided for learners, including providing different forms of content presentation, different navigation or learning paths, different learning assistance, and different evaluations.

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