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Investigation of College Students' Behavioral Learning Engagement in Online Courses*

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This study built a behavioral learning engagement model for learners in online courses in colleges and universities, and conducted an empirical study based on this model with the aim of exploring learners' learning behavior in online courses and its influence on academic performance. The study sample comprised of 301 learners who participated in an engineering online optional course offered by a comprehensive university in western China. Clustering analysis and multiple linear regression indicated following results: (1) during studying the online courses, learners' overall behavioral learning engagement is low; (2) there are differences in behavioral learning engagement and academic performance among learners of different genders and subject backgrounds; (3) according to the online behavioral learning engagement and academic performance, learners can be divided into "Active learning", "Passive learning" and "Achievement-driven"; (4) there are significant differences in the influence of behavioral learning engagement of different types of learners on academic performance.

Keywords: online courses; behavioral learning engagement; academic performance; colleges and universities; participation; concentration; interaction; performance effort; regularity

1. Introduction

With the rapid development of information technology and the advancement of the world open education resources movement, the influence of online courses is increasing day by day, and has gradually become an important starting point for teaching reform in colleges and universities. In order to reform the teaching mode, cultivate students' autonomous learning ability to meet the needs of lifelong learning, and introduce high-quality curriculum resources to enrich the curriculum system, major universities have introduced online courses one after another. However, while online courses bring opportunities to the education reform, they are confronted with a series of challenges that the management of teaching process and the teaching effect across time and space are difficult to guarantee, and the virtualization and networking of teaching make the evaluation of students' learning limited. They are also accompanied by "high dropout rate", "low participation rate" and so on. How to improve the quality of online courses and the effect of online learning has become an important issue to be studied in the field of online learning.

A large number of studies have shown that learning engagement is the key factor that affects learners' final academic performance [1–5]. In addition, learning engagement is also an important factor that affects the success of curriculum reform [6], and an important indicator for evaluating the quality of higher education [7]. Therefore, with the rapid development and popularization of various online courses and the upsurge of online learning, online learning engagement is used as an effective observation variable to observe the learning process, predict academic performance and satisfaction [8, 9], and has also gradually received widespread attention from scholars.

2. Background

2.1 Learning Engagement

Learning engagement originated from Time on Task put forward by Tyler in 1930. Subsequently, many researchers, influenced by it, launched a series of explorations and researches on learning engagement, but up to now the scholarly community has not reached a consensus on the definition of learning engagement. In the previous studies, some representative views on the understanding of this concept are as following:

- Learning engagement is the behavioral engagement that emphasizes the "task time and effort quality of participating in learning activities", or the cognitive behavior that students focuses on "learning initiative, self-monitoring and learning strategies", or the emotional conscious behavior that "students' interest, value and emotional experience in learning activities" [10].
- Learning engagement is a multivariate variable,

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which is composed of behavioral, cognitive and emotional engagement [11].

- Learning engagement is the frequency with which students participate in effective teaching practice activities, the sign of students' participation in various learning activities, and the sign of interaction within and outside the classroom as well as the whole learning career [12].

To sum up, learning engagement is a multi-dimensional concept involving behavior, cognition and emotion. It refers to the time, energy, emotion, ability and developmental resources that individuals spend in participating in learning activities. It is also the embodiment of learners' understanding of learning essence and immersion in learning activities.

2.2 Behavioral Learning Engagement

Behavioral learning engagement is one of the dimensions of learning engagement. Its concept is closely related to and different from learning engagement. Behavioral engagement emphasizes the behavior state displayed by learners in the process of participating in learning activities. It mainly focuses on the invested time and the degree of effort exerted by learners. It is an observable explicit behavior performance [13]. To some extent, this behavior performance can be regarded as the result of the joint action of cognitive and emotional engagement. Relevant researches have also shown that there is a two-way connection between behavioral engagement and cognitive and emotional engagement. Behavioral learning engagement can influence and predict later emotional and cognitive engagement [14], which is the premise of skill development, positive social interaction and emotional engagement [15].

Thus, behavioral learning engagement is the basic constituent dimension of learning engagement, and is the carrier and explicit embodiment of cognitive engagement and emotional engagement. Therefore, to a certain extent, academic performance and learning adaptability of learners can be predicted through behavioral engagement, while timely feedback and intervention of behavioral learning engagement can effectively improve academic performance.

2.3 Analysis and Evaluation of Behavioral Learning Engagement

As early as the end of the 1990s, there were researches on analyzing asynchronous interactive data of online forums to evaluate the engagement and quality of interaction among students. Later, the popularity of Learning Management System and the evolution of online teaching methods have made the learning data that can be recorded and analyzed more diversified, and the analysis of behavioral engagement has also expanded from the interactive data of forum to the various learning data of Learning Management System. Under this background, many researchers have started thinking and exploring the classification dimension or evaluation model and framework of behavioral learning engagement according to different learning situations. Fredricks et al. proposed that performance in learning should include effort, persistence, concentration, questioning and participation in discussions [16]; The student classroom engagement scale developed by Ouimet et al. proposed the dimensions of skills, participation and performance [17]; Martin divided the evaluation indexes of behavioral engagement into three aspects: persistence, planning and task management [18]; Angelino et al. proposed that behavioral learning engagement has the dimensions of active participation, interactive learning and cooperative learning [19]; Duhita Mahatmya et al. divided behavioral engagement into task time, learning behavior, participation in class and discussion [20]; Lam et al. evaluated the behavioral engagement from three dimensions of active participation, concentration and persistence [21]; Hamane proposed five dimensions of teacher-student interaction, active learning, cooperative learning, trial feedback and task time [22]; The analysis framework of online behavioral learning engagement proposed by Li Shuang et al. includes six dimensions: participation, persistence, concentration, interaction, academic challenge and self-monitoring [23]; The learning engagement model of learners in the online learning space constructed by Zhang Si et al. is divided into four dimensions: participation, concentration, regularity and interaction [24]; Liu Qingtang et al. proposed that the behavioral engagement of teachers majoring in teacher workshops should include participation, concentration, persistence and interaction [25]. Karmela et al. examined student's engagement and response time on Kahoot on Information and Communication Technologies course and analyzed the data with final grades of the course[26]. Simmons et al. proposed an engineering student engagement six-factor model. The factors are: Major Satisfaction, Academic Discipline Belonging, Major Valuing, Achievement Striving, Peer Interaction, and Positive Faculty Relationship [27].

3. Behavioral Learning Engagement Model of Learners in Online Courses

Based on the dimension analysis of behavioral engagement or the classification model of online behavioral learning engagement in the above research, considering the online courses is mainly watching videos and completing corresponding tests and homework in general, the final academic performance are usually composed of different weights such as the number of videos watched, homework grades, discussion times, examination results, etc. However, due to the flexible time and free progress of online courses, the academic performance obtained by this calculation method cannot fully reflect the real engagement of learners in the course learning process. In this study, learners' behavioral learning engagement in online courses was divided into five dimensions: participation, concentration, interaction, performance effort and regularity, and constructed a behavioral learning engagement model of learners in online courses (Fig. 1).

"Participation" refers to the learners' behavior to perform some basic operations or participate in relevant learning activities in order to comply with curriculum regulations or respond to teachers' requirements. In many studies, participative engagements regarded as the most basic behavioral learning engagement [16, 28]. Compared with the latter four types of engagement, participative engagement does not reflect the learners' in-depth learning status. It mainly reflects the learners' recognition of curriculum rules and is the premise and foundation for other dimensions.

"Concentration" refers to the efforts of learners to overcome external interference and concentrate on the content in the learning process [29, 30]. The concentration of learners on the course learning can not only reflect their ability to overcome external interference, but also reflect their emotional attitude towards the course and interest in the learning content. Therefore, concentration is an important dimension to evaluate learners' learning engagement.

"Interaction" is the communication and cooperation between learners and teachers, learners and classmates in the course learning process. Interactive behavior can reflect learners' mastery of specific learning content, cognitive level and cognitive engagement in the process of collaborative knowledge construction. In addition, interactive behavior can enhance learners' sense of belonging in the learning community and enable learners to have positive emotional experience, thus promoting learners' learning engagement [23, 31].

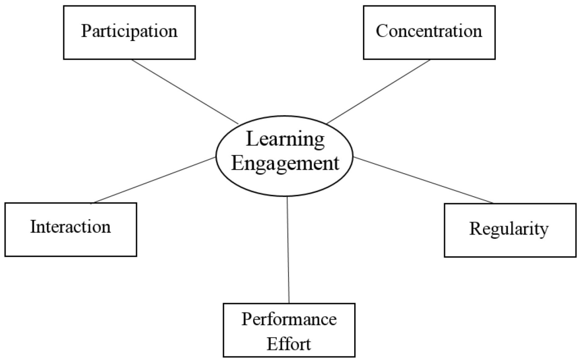

Fig. 1. The behavioral learning engagement model of learners in online courses.

"Performance effort" refers to the efforts made by learners to obtain course credit or achieve better results on the indicators related to the final performance assessment [23]. Performance effort type of engagement may include two situations: one is that learners invest more in the curriculum and have higher goals and expectations for final performance, so they will spend more time and energy to achieve better results; The other is that learners are not interested in the course itself, but only want to complete the required learning tasks in order to meet the course assessment standards and obtain the corresponding course credits.

"Regularity" is a dimension with time characteristics and refers to the stability of learners' participation in learning activities. The online learning environment is relatively free and requires higher autonomy of learners. The regularity shown by learners in the learning process can reflect learners' ability to set learning objectives and manage their own time, which can better highlight the learners' enthusiasm and efforts to the course learning [24, 32, 33].

Before the analysis of behavioral learning engagement, the specific behavioral analysis index system should be determined according to the model and data, and the data to be collected for each index as well as the measurement method of it should be explained. In this study, behavioral learning engagement is divided into five dimensions: participation, concentration, interaction, performance effort and regularity. Each dimension contains several secondary indicators. The detailed description of the variables indicated by each secondary indicator is shown in Table 1.

4. Methodology

4.1 Participants

In this study, an engineering online course offered by a comprehensive university in western China was taken as an example. This course is an elective course to popularize agricultural engineering knowledge for college students. 305 students who participated in the course during the spring semester of 2017–2018 were taken as data collection samples, excluding invalid samples, the effective sample number is 301. The rejected invalid samples

Table 1. Indicator system of learner behavioral learning engagement in online courses

Engagement type	Analysis indicators
Participation	Number of times to view course notifications
	Number of participation in learning activities
	Number of submitted chapter test
Concentration	The number of times a video has been played in its entirety in continuous time
	The number of got the quiz question wrong while watching the video
	The ratio of video viewing time to video length
	Total video viewing time
	Chapter test scores
Interaction	Number of posts and words
	Number of replies and words
	Content depth of posts and replies (use knowledge to construct interactive analysis model and divide them into different levels)
Performance effort	Number of exams to the learning page
	The number of videos watched
	The number of videos watched in full
	Number of submitted homework
	Homework grades
	Exam results
Regularity	The time interval between submitting and publishing of homework
	Average access days interval
	Average number of visits per attendance day
	The duration of final examination

were students who had never participated in any learning activities in the course and ended up with a score of 0.

In the 301 valid samples, the gender distribution was 85 males and 216 females. Judging from grade distribution, the number of freshmen accounts for 97% of the total sample, while the number of sophomores, juniors and seniors students each accounted for 1% of the total sample. The distribution of subject backgrounds is 186 students majoring in science and engineering, 66 students majoring in humanistic and social science, and 49 students majoring in arts and physical education.

4.2 Data Collection and Preprocessing

The data collected in this study include learners' online learning behavior data and academic performance. Academic performance can be directly exported in the platform background, while the collection and preprocessing of online learning behavior data can be divided into: explicit operating behaviors (refers to all kinds of fixed and objective log data generated in the online learning process of learners automatically recorded by the platform, such as video viewing times, login time, job submission times, etc.) collection and preprocessing and implicit interactive behaviors (refers to the specific interactive contents such as discussion, answering questions, communication and evaluation that cannot be directly quantified and analyzed by data statistical methods and need to be coded and converted into corresponding cognitive behaviors according to certain interactive models.) collection and preprocessing.

Among them, the explicit operating behavior data is mainly obtained by extracting relevant original data from the background and calculating with corresponding methods. The implicit interactive behaviors are coded manually after counting all learners' posts and replies in the course discussion area. In order to cover all interactive texts and ensure the comprehensiveness of the coding results, this study divided the collected post data into two categories: "related to the learning theme" and "unrelated to the learning theme". Posts related to learning topics were coded according to Gunawardena's hierarchical model of interactive knowledge construction, while posts unrelated to learning topics were classified into three categories: "social emotional communication", "activity process consultation" and "no substantial content" (Table 2).

4.3 Data Analysis

The main analysis methods in this study include descriptive statistical analysis, difference significance test, clustering analysis and multiple linear regression. Among them, descriptive statistical analysis was used to analyze the basic situation of learners' behavioral learning engagement in various dimensions. The difference significance test was used to examine the differences in behavioral learning engagement in different dimensions of learners

Table 2. Coding system of implicit interaction behavior

Type	Coding	Behavior	Interpretation
Related to the study theme	Y1	Share/compare discussion topic information	Learners share information with each other, state their personal opinions on the topic of discussion or ask questions about problems encountered in learning
	Y2	Find and explore inconsistencies between ideas	Learners discover and analyze inconsistencies with their own cognition from the information shared by others and their stated opinions, so as to deepen their understanding of the problem
	Y3	Meaning negotiation and collaborative knowledge construction	After receiving others' suggestions or different viewpoints, learners re-examine their own viewpoints and construct knowledge through meaning negotiation
	Y4	Test and revise the knowledge of collaborative construction	Learners test and modify the constructed ideas
	Y5	Apply newly constructed knowledge	The learner reached an agreement, indicating that their understanding and thinking have changed after the collaborative discussion, and they began to apply the newly constructed knowledge
Unrelated to the study theme	N1	Social emotional communication	The learner agrees with others or expresses gratitude for the information shared by others, such as: "Great, thank you teacher, great"
	N2	Activity progress consultation	The learner asks about the requirements and progress of related learning activities or tasks
	N3	No substance	Some meaningless symbols and expressions, such as "1" "."

with different gender, different subject backgrounds and different participation in course discussion. Cluster analysis was used to explore the characteristics of behavioral learning engagement and academic performance of different types of learners. Multiple linear regression was used to analyze the relationship between learners' online learning behavior and academic performance in all dimensions. All data processing and analysis work were completed by SPSS24.0.

5. Results

5.1 Descriptive Statistical Analysis

The basic situation of learners' behavioral learning engagement in every dimension in online courses is shown in Table 3. From the descriptive statistical results, it can be seen that:

5.1.1 Participation Dimension

During the course, the teacher issued a total of 9 course notices, and the average number of times the learners checked the course notices reached 8.5, indicating that the learners basically checked each course notice. The average number of learners' participation in the course activities is 3.63, while the total number of course activities is 6, which show that learners' participation in this dimension is somewhat insufficient. Chapter tests are objective test questions randomly inserted after learning videos of some key chapters according to specific teaching contents. The course contains 10 chapter tests, and the average number of tests submitted by learners is 8.81.

5.1.2 Concentration Dimensions

The number of times the video is completely played in a continuous period of time refers to the fact that after the learner clicks on the video to learn, there is no long-term pause in the middle. After watching the video continuously until the end, the statistical result show that the average value is 37.02, while the total number of videos is 51, which indicates that it is more common for learners to pause or quit learning in the process of watching the video. In all the learning videos, 13 test questions were popped up, and all the test questions were judgment questions or multiple-choice questions. The average number of test questions popped up in the wrong videos was 6.51. It can be seen that the learners did not completely focus on the teaching content when watching the learning videos. The average total time spent watching videos by learners is 990 minutes, which is greater than the sum of the original time spent watching all videos 886 minutes, indicating that learners have playback phenomenon in video learning, which is consistent with the average value of video rumination ratio greater than 100%. The total score of chapter tests is 100, and the average score of learners is 76.70, which is relatively low.

5.1.3 Interaction Dimension

The average number of times posted by the learners is 0.02, which show that the learners will not

Table 3. Basic situation of learners' behavioral learning engagement

Dimension		M	SD
Participation	Number of times to view course notifications	8.50	1.464
	Number of participation in learning activities	3.63	1.449
	Number of submitted chapter test	8.81	1.651
Concentration	The number of times a video has been completely played in a continuous time	37.02	8.455
	The number of wrong answers to the quiz questions popped up in the video	6.51	10.917
	Video View Rumination Ratio	1.111	0.703
	Total video viewing time (minutes)	990.122	579.899
	Chapter test scores	76.699	20.121
Interaction	Number of posts	0.02	0.151
	Number of replies	0.60	3.442
	Posting words	55.71	67.141
	Replies words	10.639	7.422
Performance efforts	Number of visits to the learning page	164.09	105.874
	Number of video views	50.53	3.410
	The number of videos watched in full	48.714	5.526
	Number of submitted homework	3.58	0.882
	Homework grades	89.118	19.434
	Exam results	80.06	17.527
Regularity	Average homework submission time interval (hours)	30.135	13.726
	Average access days interval	7.565	5.364
	Visits per attendance day	7.639	5.074
	The duration of final examination (minutes)	40.028	23.023

actively post to communicate with teachers and other learners. The average number of replies from learners is 0.6. Although it is higher than the number of posts, it also means that the average number of replies per learner is less than 1. Moreover, the replies from learners are basically directed at posts sent by teachers, and there is little communication between learners and each other. Among all the learners, 7 took part in the posting, and each person only posted once, with an average of 55.71 words per posting. However, the content type and word number of each learner's posting are quite different, and the word number difference can be seen from the standard deviation of this variable. A total of 36 learners participated in the reply, with an average of 10.639 words per reply.

After encoding 187 posts in the forum according to the previously constructed implicit interactive behavior encoding system, it is found that the total number of Y1–Y5 posts is less than that of N1–N3 posts, i.e. the number of posts not related to the learning theme is more than the number of posts related to the learning theme in the posts published or replied by the learner, and among the posts related to the learning theme, Y1 type posts are more, and some belong to Y2, while the number of posts of Y3, Y4 and Y5 types are all 0.

5.1.4 Performance Efforts Dimension

The average number of visits to the course by learners during the 15-week study reached 164.09 times, but the standard deviation show that the total number of courses visited by different learners varies greatly. The average number of videos watched by learners is 50.53, which is basically close to the total number of learning videos, 51, but the average number of full videos watched is 48.71, which indicates that some learners will not play all the learning videos they started watching completely. The average number of assignments submitted was 3.58, which was close to the total number of assignments 4, indicating that the learners had higher enthusiasm for submitting assignments, and the average performance of assignments was 89.1180, which was significantly higher than that of chapter tests in the focus dimension. A total of 237 learners took part in the final online examination, with an average examination score of 80.06 points.

5.1.5 Regularity Dimension

The average time interval between the submission of homework by learners and the assignment by teachers is 30.13 hours, exceeding 1 day. The average time interval between visits is 7.56 days, which indicates that learners usually log into the course twice with a time interval of more than one week. Compared with the traditional offline courses, which have to arrange class hours at a fixed time every week, learners in online courses lack regularity in the arrangement of course learning time. On the other hand, in all the days when the learner participates in the course study, the average number of visits to the course study page per attendance day reaches 7.63, which indicates that the learner prefers to complete the study tasks in the attendance day. The prescribed time for the online final examination is 60 minutes, and the average time for the learners taking the examination is 40 minutes. The time length is basically reasonable, but the standard deviation of the data variable reaches 23 or more, which indicates that different learners have great differences in the time length for the examination.

5.2 *Difference Significance Test*

5.2.1 *Gender Differences*

In order to explore whether there are differences in online learning behavioral learning engagement and final academic performance of learners of different genders, independent-sample T test was used to compare and analyze the learning behavior variables of learners of different genders in every dimension and final comprehensive assessment results. The analysis results show that there are significant differences between male and female learners only in the two behavior variables of the number of assignments submitted in the dimension of performance effort and the average time interval of assignments submitted in the dimension of regularity ($p < 0.05$). And through descriptive statistical results, it can be seen that the average number of assignments submitted by girls is significantly higher than that of boys (3.66 for girls and 3.38 for boys), and the average time interval between assignments submitted by girls is shorter than that of boys (28.7213 for girls and 33.744 for boys).

5.2.2 *Differences in Subject Backgrounds*

In order to explore whether there are differences in learners' online behavioral learning engagement and academic performance from different subject backgrounds, the learning behavior variables in different dimensions of learners from different subject backgrounds are compared with the final results by using one-way ANOVA. The analysis results show that there are significant differences between learners from different subject backgrounds in the two behavior variables of the number of complete video plays in continuous time and chapter test scores in the concentration dimension ($p < 0.05$); In the dimension of performance effort, there are significant differences in the number of assignments submitted, the results of assignments and the grades of examinations among learners from different disciplines ($p < 0.05$); In the dimension of regularity, the average time interval of submitting homework, the average time interval of visiting days, and the duration of examination are significantly affected by the learners' subject background ($p < 0.05$); Subject background has a significant effect on learners' comprehensive performance ($p < 0.05$).

Descriptive statistics were carried out on the means of learning behavior variables with significant differences among learners from different subject backgrounds. From the descriptive statistics results, it can be concluded that: in the dimension of concentration, arts and physical education learners have slightly higher engagement, but in the dimension of performance effort, arts and physical education learners are less motivated to submit homework, and their homework and examination results are lower than the average of the whole class. Judging from the average time interval of submitting homework in the dimension of regularity, the timeliness of submitting homework for arts and physical education learners is higher than that for other learners, but the average time interval of visiting days for arts and physical education learners is more than 10 days, which indicates that these learners have no regularity in learning arrangement and do not participate in the course learning for a long time. Therefore, it can't be ruled out that the higher average number of continuous watching of course videos in the dimension of concentration is due to the surprise completion of learning tasks at the later stage of the course. The duration of the examination is only half of that of science and engineering learners and humanistic and social science learners, indicating that they do not attach enough importance to the examination. In addition, the comprehensive scores of arts and physical education learners are obviously lower than those of science and engineering learners and humanistic and social science learners, and the comprehensive scores of science and engineering learners are slightly higher than those of humanistic and social science learners.

5.2.3 *Explicit Learning Behavior Differences of Learners with or without Interaction*

From the previous analysis of the basic situation of learners' behavioral learning engagement, it can be seen that learners' engagement in the dimension of interaction is generally low, and only a small proportion of learners have posted or replied in the forum. In order to explore whether there is any difference in behavioral learning engagement and final scores between the learners who participated in the course discussion and those who did not participate, all learners were divided into two types: those who posted or responded in the

forum and those who have never participated in the discussion. The online learning behaviors and final comprehensive scores of the two types of learners were tested by independent-sample T test.
The analysis results show that there are significant differences between the learners who participated in the course discussion and the learners who did not only in the number of courses activities in the dimension of participation, the number of assignments submitted in the dimension of performance effort and the average access time interval in the dimension of regularity ($p < 0.05$), and there are also significant differences in the final comprehensive scores of the two types of learners ($p < 0.05$).

By analyzing the means of several behavior variables with significant differences between the two types of learners, it can be seen that the mean of learning activities, the mean of assignments submitted, and the average comprehensive scores of the learners participating in the discussions are higher than those of the learners not participating in the discussions, and the average access time interval is lower than that of the learners not participating in the discussions.

5.2.4 Explicit Learning Behavior Differences of Learners with Different Posts Depth

The above research results show that there are some differences in behavioral learning engagement and final academic performance between the learners who participated in the course discussions and the learners who did not. In order to further explore whether there are differences in behavioral learning engagement and academic performance between the learners who participated in the discussions and have different posts content depth, one-way ANOVA was used to compare all learning behavior variables and comprehensive scores of three types of learners whose posts are related to learning themes, posts are unrelated to learning themes, posts or replies contain both learning theme-related and learning theme-independent content. The results of comparative analysis show that there is no significant difference in all learning behaviors among the three types of learners ($p > 0.05$), namely, the content of posts is related to the learning themes, the content of posts is unrelated to the learning themes, and the posted or returned posts contain both the content related to the learning themes and the content unrelated to the learning themes ($p > 0.05$).

5.3 K-Means Clustering Analysis

The K-means clustering algorithm was applied to cluster the learning behavior variables of each dimension in the online behavioral learning engagement model and the comprehensive scores of learners, so as to explore the behavioral learning engagement characteristics and scores of different types of learners. In order to achieve better cluster effect, this paper combined elbow method and silhouette coefficient method, two relatively mainstream methods to determine the number of clusters K, to select the value of K, and concluded that the best cluster coefficient should be 3. The data of 294 samples remaining after standardization and elimination of missing values were analyzed by K-means cluster in SPSS24.0, and the number of cases included in the 3 clusters was 138, 59 and 97 respectively, assuming that the number of clusters K was 3.

In order to judge the behavioral learning engagement and comprehensive scores of these three types of learners in each dimension more specifically, all cluster members were mapped to their original behavior data, and the mean of all behavior variables and the mean of comprehensive scores of each category in each dimension were calculated (Table 4).

From the analysis results, it can be seen that in the whole learning process, except that the behavioral indicators of the concentration are lower than those of the latter two types of learners, the behavioral learning engagement of the other dimensions is better than that of the latter two types of learners, and is higher than the average level of the class, and the final academic performance is also better. Therefore, this study regards this kind of learners as "active learning type". The participation and regularity of type 2 learners in curriculum activities are lower than that of type 1 learners and slightly higher than that of type 3 learners. The average value of behavioral learning engagement indicators in all dimensions is near the average value of class. However, since most of these learners did not take the final examination, resulting in the lowest comprehensive scores among the three types of learners, they can be regarded as "passive learning type". Type 3 learners have the lowest degree of participation and enthusiasm in curriculum learning activities and the weakest regularity in curriculum learning, but their comprehensive scores are in the middle level among the type 3 learners. Therefore, they can be regarded as "achievement-driven".

According to whether the relationship between behavioral learning engagement and academic performance is positive or not, type 1 learners belong to a positive relationship between behavioral learning engagement and academic performance, accounting for 47% of the total sample. Type 2 learners' lower comprehensive scores due to their failure to take the final examination can be regarded as abnormal situations. The third type of learners

Table 4. Means of behavior variables in each category

Behavior variable		**Class 1**	**Class 2**	**Class 3**
Participation	Number of times to view course notifications	8.76	8.41	8.32
	Number of participation in learning activities	4.34	3.41	2.91
	Number of submitted chapter test	9.40	8.51	8.26
Concentration	The number of times a video has been completely played in a continuous time	35.77	38.34	38.00
	The number of wrong answers to the quiz questions popped up in the video	6.42	6.37	7.04
	Video View Rumination Ratio	1.071	1.215	1.116
	Total video viewing time (minutes)	950.786	1056.744	1006.954
	Chapter test scores	75.903	76.944	77.821
Interaction	Number of posts	0.04	0.02	0.00
	Number of replies	1.14	0.24	0.08
	Posting words	61	24	0.00
	Replies words	37.428	35.5	23.5
Performance efforts	Number of visits to the learning page	193.30	151.15	137.80
	Number of video views	51.00	50.49	50.33
	The number of videos watched in full	49.46	48.19	48.35
	Number of submitted homework	3.99	3.39	3.36
	Homework grades	96.365	85.155	82.138
	Exam results	84.93	0.59	73.00
Regularity	Average homework submission time interval (hours)	23.736	31.831	38.476
	Average access days interval	5.664	8.483	8.852
	Visits per attendance day	7.653	7.095	7.329
	Duration of examination (minutes)	50.167	0.516	51.923
Average of comprehensive score		94.207	72.152	82.555

have the worst behavioral learning engagement, but they have achieved relatively good scores. They belong to the non-positive relationship between behavioral learning engagement and academic performance, accounting for 33% of the total sample.

5.4 Multiple Linear Regression

5.4.1 Multiple Regression Analysis of Learners' Overall Online Learning Behavior and Academic Performance

In order to explore the degree of influence into different behavior variables in online behavioral learning engagement on academic performance, Pearson correlation coefficient method was used to analyze the correlation between all behavior variables of sample and comprehensive scores. The analysis results show that 11 behavior variables out of 22 learning behavior variables in five dimensions have significant linear relationship with comprehensive scores. According to the conclusion of correlation analysis, after eliminating the behavior variables that have no significant linear relationship with comprehensive scores, 11 behavior variables that have significant linear relationship with comprehensive scores are taken as independent variables, and comprehensive scores are taken as dependent variables to establish a multiple linear regression model. A total of 7 variables finally entered the regression equation (Table 5). The seven behavior variables mainly come from the dimensions of performance effort and regularity, among which the partial regression coefficient of assignment submission times is much larger than other explanatory variables.

5.4.2 Multiple Regression Analysis of Online Learning Behavior and Academic Performance of Different Types of Learners

To further explore the influence of various behavior variables on the academic performance of the three types of learners with different engagement obtained from clustering analysis, correlation analysis and multiple regression analysis were carried out on all learning behavior variables and comprehensive scores of each type of learners, respectively. The results are as follows:

Among the 22 learning behavior variables of "active learning" learners, only the chapter test scores (0.213*), number of visits to the learning page (0.220**), number of submitted homework (0.236**), homework grades (0.736**), and exam results (0.677**) have significant linear correlation with comprehensive scores. A multiple regression

Table 5. Multiple regression coefficients for online learning behaviors and academic performance

Model	B	Standard error	Beta	t	Significance	Tolerance	VIF
(constant)	–16.232	3.252		–4.991	0.000		
Number of submitted homework	6.688	0.246	0.406	27.159	0.000	0.533	1.875
Exam results	0.163	0.004	0.499	43.825	0.000	0.921	1.086
Homework grades	0.204	0.008	0.327	25.911	0.000	0.749	1.334
Number of video views	0.993	0.062	0.180	15.925	0.000	0.933	1.072
Number of visits to the learning page	0.005	0.001	0.044	3.709	0.000	0.849	1.178
Submit homework intervals	–0.046	0.010	–0.054	–4.713	0.000	0.907	1.103
Interview days interval	–0.105	0.034	–0.042	–3.086	0.002	0.657	1.523

Note. Dependent variable: comprehensive score.

equation between these five variables and comprehensive scores was established. The behavior variables that eventually entered the regression equation all came from the dimension of performance effort, namely, homework grades, exam results, number of submitted homework and number of visits to the learning page. Among them, the explanation variable with the largest partial regression coefficient was homework submission times (Table 6).

Among the 22 learning behavior variables of "Passive learning" learners, there are 8 behavior variables that have significant linear correlation with comprehensive scores, namely, the number of course activities (0.267*), number of visits to the learning page (0.269*), the number of video views (0.331*), the number of complete video views (0.299*), the number of submitted homework (0.803**), the homework grades (0.599**), the time interval for submitting homework (0.477**), and the time interval for visiting days (0.396**). Taking these eight learning behavior variables as independent variables and comprehensive scores as dependent variables, a multiple regression equation is established. The behavior variables entering the final regression equation are: the number of submitted homework, homework grades, the number of videos watched and the interval of visit days (see Table 7). Among the four explanatory variables, the interval of visit days comes from the regular dimension, and the other three come from the performance effort dimension. The partial regression coefficient of the number of job submissions is much larger than that of other explanatory variables.

Table 6. Multiple regression coefficients of learning behaviors and academic performance of "active learning" learners

Model	B	Standard error	Beta	t	Significance	Tolerance	VIF
(constant)	23.541	3.010		7.820	0.000		
Homework grades	0.339	0.011	0.636	30.791	0.000	0.963	1.039
Exam results	0.148	0.005	0.608	29.654	0.000	0.975	1.026
Number of submitted homework	6.201	0.736	0.173	8.427	0.000	0.968	1.033
Number of visits to the learning page	0.004	0.001	0.113	5.531	0.000	0.984	1.016

Note. Dependent variable: comprehensive score.

Table 7. Multiple regression coefficients of learning behavior and academic performance of "Passive learning" learners

Model	B	Standard error	Beta	t	Significance	Tolerance	VIF
(constant)	–25.347	7.787		–3.255	0.002		
Number of submitted homework	7.483	0.436	0.698	17.177	0.000	0.713	1.402
Homework grades	0.190	0.017	0.421	11.504	0.000	0.879	1.137
Number of video views	1.136	0.151	0.267	7.506	0.000	0.935	1.069
Interview days interval	–0.170	0.077	–0.088	–2.208	0.031	0.738	1.354

Note. Dependent variable: comprehensive score.

Table 8. Multiple regression coefficients of learning behaviors and academic performance of "achievement-driven" learners

Model	B	Standard error	Beta	t	Significance	Tolerance	VIF
(constant)	–15.081	4.758		–3.170	0.002		
Number of submitted homework	6.898	0.379	0.541	18.215	0.000	0.787	1.271
Homework grades	0.180	0.013	0.406	13.381	0.000	0.753	1.328
Number of video views	0.986	0.092	0.287	10.748	0.000	0.972	1.029
Exam results	0.137	0.014	0.270	10.101	0.000	0.967	1.034

Note. Dependent variable: comprehensive score

Among the 22 learning behavior variables of "achievement-driven" learners, the number of replies (–0.267**), the words of replies (–0.270**), the number of video views (0.375**), the number of assignments submitted (0.771**), the assignment results (0.748**), the examination result (0.400**), the submission interval (0.243**) and the access interval (–0.353**) have significant linear correlation with the comprehensive scores. A multiple linear regression equation was established for these 8 learning behavior variables and comprehensive scores. Only 4 behavior variables entered the final regression equation model, namely, the number of submitted homework, homework grades, the number of videos watched and exam results (Table 8). The four explanatory variables are all from the dimension of performance effort, and the explanatory variable with the largest partial regression coefficient is still the number of submitted homework.

6. Discussion

6.1 The Overall Behavioral Learning Engagement of Learners in Online Courses is Low

In the online course, the basic situation of learners' behavioral learning engagement in each dimension is: the level of engagement in the dimension of participation is general, that in dimensions of concentration, interactions and regularity is lower, and in the dimension of performance effort is higher. In general, learners pay more attention to the participation of learning activities that are related to academic performance in the learning process, and the overall behavioral learning engagement is low [34]. The specific performance is: the concentration of learners watching the learning videos is not enough; the participation in the online discussion is low, even if it is involved in the discussion, the main interactive object is the teacher, there is basically no interaction between the learners; the learning regularity is poor, many learners do not visit the learning page for more than ten days, and once they log in, they will focus on multiple learning tasks. This result confirms the previous research conclusions drawn from the previous survey of online elective courses in colleges and universities: students pay less attention to online elective courses, and their learning is less proactive. Most students only learn to earn credits, and even some students only open the learning interface without learning; the student's learning schedule is unreasonable and lacks learning autonomy [35]; the function of communication and discussion provided by the online elective course does not really play a role, and the real purpose of students participating in the discussion is not to communicate about learning problems, but to save the number of discussion and complete tasks, or get the discussion points [36].

6.2 Differences in Behavioral Learning Engagement between Learners with Different Characteristics

The results of the study show that: (1) The learning behavior of the students in different genders in the online course is not much different, but the enthusiasm of girls to submit homework is significantly higher than that of boys. This result is basically consistent with the conclusions of the related research that the female students' online learning behavior is higher than that of the male students [37, 38]. (2) The enthusiasm and regularity of the learners with major in arts and physical education participating in the learning activities in the course learning are not as good as those of other learners, and the academic performances are also the lowest. There is no significant difference in the learning engagement of the science and engineering learners and humanistic and social science learners, but the results of the homework and overall scores of science and engineering learners are slightly higher than those of the humanistic and social science learners. This research result is consistent with the conclusion that Fu Gang Shan et al. found in the research that learners from different disciplines and backgrounds have significant differences in various online learning behaviors, and most arts and physical education learners have lower scores than science and engineering learners and humanistic and social science learners [37]. (3) The learners participating in the discussion have higher engagement in the participation dimension, performance effort dimension and regular dimension than the learners who did not participate in the discussion, and they will also eventually achieve a better overall score. This is consistent with the better results achieved by students who actively interact with teachers and peers mentioned in previous research conclusions [23].

6.3 Some Learners' Behavioral Learning Engagement are Not Positively Related to Academic Performance

According to the results of cluster analysis, 33% of learners' behavioral learning engagement has a non-positive relationship with academic performance. This research result is similar to that of Zong yang et al. in the logistic regression analysis of MOOCs learning behavior and learning effect[39], which found that half of the learners have lower participation in the learning process, but they have achieved better results in the end. There are two reasons for this: First, the data indicators listed in this study do not fully reflect the learner's learning engagement. Such learners may not adapt to online learning and will use other methods instead of learning online; secondly, the assessment indicators of the course can't accurately reflect the actual learning effect of learners, and will give some learners with the purpose of completing tasks to obtain credits opportunities for opportunistic. Therefore, the online course should strengthen the evaluation mechanism in the process of development, not only staying in the number and duration, but also in-depth study of the learner's learning regularity, interactive content, job quality, etc., and timely intervention.

6.4 Differences in the Impact of Different Types of Learners' Behavioral Learning Engagement on Academic Performance

Through multiple regression analysis, it is found that the multiple regression equations of learners' overall learning behavior variables and comprehensive scores and the multiple regression equations of three different categories of learners' learning behavior variables and comprehensive scores contain two common explanatory variables: the number of job submissions and the results of the homework, and the number of job submissions are the largest explanatory variables of the partial regression coefficient in each regression equation. This is completely consistent with the research results obtained by Li Shuang et al. that the number of job submissions had the strongest effect on performance prediction [23]. This show that whether the assignment is completed or not has a greater impact on the learners' final scores [40]. The reason why the effect of the homework grade on the comprehensive score is less than the number of job submissions may be that the homework is not only a test of the learner's learning effect, but also a process for the learner to learn again and deepen the memory. Some learners may have a vague memory of the relevant knowledge points when completing the homework, which leads to the wrong answer to lower the homework grades, but this will enable the learner to grasp the knowledge point more firmly and no longer make mistakes during the test.

In addition, there are some differences between the regression equations of different categories of learners and the overall regression equation:

(1) The "active learning class" learner's regression equation lacks the number of video views, the submission time interval, and visit days interval. The reason for this difference may be that the overall characteristic of this kind of learners is their high enthusiasm and devotion to participate in the learning activities of the course. Therefore, when the number of video views is taken as the most basic indicator to measure whether the learners have completed the learning tasks, there is no difference between the learners; and this kind of learners participating in the course learning activities with strong regularity, so the time interval for submitting assignments and the interval between visits will not become factors that affect the final scores of such learners.

(2) The regression equation of the "passive learning" learners reduces exam results, number of visits to the learning page, and time interval for submitting the assignment. The reason for this difference is that the learners are basically not involved in the final exam, and the comprehensive scores are only composed of the performances of participating in the course activities and homework grades, so the exam results will not affect the overall scores; in addition, because of the enthusiasm and regularity of the class learners participating in the course learning is relatively good, number of visits to the learning page and the time interval for submitting homework are two variables that can reflect the enthusiasm of learners to participate in the learning of the course, and there will not be much difference in these variables among such learners. The situation of this type of learners is consistent with the phenomenon mentioned by Zhang Huai and others in the survey of the current situation of online elective courses offered in colleges and universities that

some students will not take the final examination after finding that they have achieved qualified results after attending the courses every semester [41].

(3) The regression equation of the "achievement-driven" learners reduces the number of learning page visits, the time interval for submitting homework, and the time interval for visiting days. Because this type of learners have low participation in the ordinary course, the time interval of accessing the course learning page and the time interval for submitting the homework are long, which belongs to the utilitarian learners whose purpose are achieving good academic performances by completing the learning task before the end of the course. Therefore, the learning behaviors that affect academic performance are mainly concentrated in the performance effort dimension, while the number of visits to the learning page, the time interval for submitting assignments, and the interval between visits, three explanatory variables reflecting the regularity of learning, have no influence on the academic performance of such learners.

7. Conclusion

Although the introduction of online courses has enriched the curriculum resources and brought convenience to teaching, its characteristics across time and space have increased the difficulty of teachers' supervision and relaxed the control of learners' learning. When learners' self-management ability is weak, there will be problems such as insufficient engagement in learning and poor learning results. From the perspective of learning engagement, this paper constructs a learner's behavioral learning engagement model in online courses, and takes an online elective course opened by a comprehensive university in western China as an example. The conclusions show that in the online course learning, the learners pay more attention to the level of academic performance, but the learning behavior is generally; the learners with different genders and different academic backgrounds have different learning behaviors, and the learners who participate in the course discussion has higher enthusiasm, and their final results will be better, but the level of interaction between learners is relatively shallow; the relationship between behavioral learning engagement and academic performance of different types of learners is different; the behavioral variables that have a stronger influence on academic performance mainly come from the performance effort dimension, followed by the regularity. Therefore, in the progress of the online course, teachers should regularly review the learner's learning progress, intervene timely, and try to avoid the learners' sudden completion of the task in the later stages of the course; in addition, the final course assessment should not only stay on the surface data, it should be investigated from the learner's concentration of learning, interaction, and enthusiasm for participating in activities. There are still some shortcomings in this research: First, because the sample data is only from one course of a university, the research conclusion may be difficult to apply to a wider range; secondly, the behavioral learning engagement is only one of the dimensions of the learner's learning engagement. In future research, cognitive and emotional engagement should be combined to present the learner's engagement in online courses more comprehensively.

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