On the Cognitive Load of Online Learners With Multi-Level Data Mining

Lingyan Liu, School of Information Science and Technology, China
Bo Zhao, Key Laboratory of Educational Informatization for Nationalities, Ministry of Education, China*
Yiqiang Rao, Key Laboratory of Educational Informatization for Nationalities, Ministry of Education, China

ABSTRACT

A lot of studies have shown that there is an “inverse U-curve” relationship between learners’ grades and cognitive load. Learners’ grades are closely related to their learning behavior characteristics on online learning. Is there any relationship between online learners’ behavior characteristics and cognitive load? Based on this, the data of research are obtained from the professions and applied sciences on the Canvas Network platform. The multi-level data mining technology is used to analyze and mine the relationship between grades and online learners’ behavior characteristics layer by layer. The results show that there is an “inverse U-curve” relationship between grades and “nevents.” Therefore, the research attempts to map “nevents” to the online learners’ cognitive load, which makes the online learners’ cognitive load can be quantitative analysis. Research results also prove that multi-level data mining technology can be used to mine the special learning rules hidden behind the data effectively.

KEYWORDS

Cognitive Load, Grade, Learning Analytic, Multi-Level Data Mining, Online Learning Behavior Characteristics

INTRODUCTION

As early as 2012, massive open online courses have proliferated. After a decade of development, online learning has begun to take shape. According to relevant statistics, as of November 18, 2013, Coursera has 5.4 million registered users, Udacity has more than 1 million registered users, and EDX has more than 900 thousand registered users (Laura Pappano, 2012). Online learning has become a popular way of learning. Many people are attracted, including researchers, educators, and learners. Until 2020, due to the sudden outbreak of COVID-19, online learning was rapidly propelled to the forefront of the education era. It became an effective method for teachers and learners to take continuous teaching and learning. However, with the continuous expansion of the scale of online learning, there are common phenomena, such as high dropout rates (Kizilcec et al., 2017), low participation rates (Orji et al., 2020), low completion rates (Khalil & Ebner, 2017), and high back accessing rates (Wu et al., 2018) among learners of online learning.

The most interesting phenomenon is learners’ frequently back accessing behavior. Bing Wu and Xiao (2018) found that 15.68% of the accessing activities are back accessing, and each learner has...
an average of 1.33 times back accessing behavior. So why do learners spend a lot of time on back accessing activities? The direct reason may be that learners have missed some learning resources, or have forgotten important learning content in the process of learning, which makes it hard for learners to continue learning. However, the essential reason may be that learners need to deal with more and more information in online learning. In the process of information processing, the capacity of information work is limited (subject to working memory) (Paas et al., 2010). If the amount of information received by learners exceeds the capacity of working memory, an additional cognitive load will be generated (Sweller et al., 1998), which will reduce the learning efficiency of learners and lead to continuous back accessing behavior. Therefore, it can be speculated cognitive overload of learners may be caused by a large number of learning tasks.

At present, the relationship between learners’ cognitive load and grade has been widely studied (Atiomo, 2020; Kirschner et al., 2011; Tzafilkou et al., 2021). Fairclough et al. (2005) pointed out that when the cognitive load exceeds the total cognitive load of the individual, job performance will decline to some extent. De Waard and Brookhuis (1996) further pointed out that the relationship between task demand and task performance is an “inverse U-curve” relationship.

With the rapid development of online learning, the measurement of online learners’ cognitive load has become an urgent problem in the development of personalized online learning. Based on this, multi-level data mining technology was used in this study to analyze and mine the relationship between grades and online learners’ behaviors layer by layer, using data obtained from the Canvas Network platform. The purpose was to map the specific learning behavior characteristic to the cognitive load by exploring the relationship between learning behavior characteristics and grades. The experimental results show that there is an “inverse U-curve” relationship between grades and “nevents.” Therefore, “nevents” can be mapped to the cognitive load of online learners. The experimental results also show that the special learning rules hidden behind the data can be effectively mined by the multi-level data mining technology.

**BACKGROUND**

Online learning is characterized by a large number of digital resources. In the process of learning, multiple tasks must be processed at the same time by learners’ working memory. Due to the limited capacity of working memory, exerting appropriate cognitive load on working memory has been becoming the key to the success of online learning (Haryana et al., 2022). However, there is little research based on the cognitive load of online learners at present, so this article will serve as a preliminary exploration.

**Theory of Cognitive Load**

In the 1980s, Professor John Sweller proposed the cognitive load theory based on the limitations of working memory (Kalyuga & Sweller, 2004). The theory states that cognitive load is a cognitive resource consumed by learners in the process of information processing (Ammarkrud et al., 2019). When learners acquire new knowledge, working memory is used by them, and its capacity and duration are limited. If learners need to process information that exceeds the individual’s information work capacity, the cognitive load will be generated (Haryana et al., 2022).

The cognitive load includes intrinsic cognitive load, extraneous cognitive load, and germane cognitive load (Sweller et al., 1998). Germane cognitive load is required for learning, intrinsic cognitive load is related to the complexity of learning knowledge, and extraneous cognitive load is related to the real-time requirement of learners. Therefore, to improve the performance of online learners, it is necessary to exert an appropriate extraneous cognitive load on online learners.

Three commonly used cognitive load measurement methods are: 1). subjective assessment measurement, 2). task performance measurement, and 3). physiological measurement. Subjective assessment measurement was a commonly used method in the past (Sweller et al., 2019). With
the development of technology, physiological measurement has been widely used. Physiological measurement mainly relies on the evidence of physical reactions caused by mental needs (Sweller et al., 1998). Therefore, physiological measurement is extremely sensitive to the body’s response, which sometimes adds unnecessary false information to the experiment. Task performance measurement methods are divided into primary task measures and secondary task measures. The primary task measurement is to evaluate the cognitive load requirement of the task by directly measuring the achievement of the learner in completing the assigned task. Therefore, the measurement idea of the primary task measurement is more suitable for the measurement of online learners’ cognitive load.

Application of Cognitive Load

With the continuous development of technology, measurement of the cognitive load has been widely used in various fields. The application of cognitive load in education can be discussed from three aspects: 1). instructional design, 2). learning environment, and 2). learning materials.

In terms of instructional design, the appropriate intervention has a positive effect on cognitive load. The application of cognitive load in instructional design is mainly realized by adding corresponding teaching interventions. Dinçer and Doğanay (2017) researched the impact of instruction subjects on learners’ academic success in computer-assisted instruction, using comparative experiments. The results show that the intervention of instruction subjects has a positive effect on the cognitive load of learners. Therefore, instruction designers should provide corresponding instruction interventions for learners.

In terms of the learning environment, the utilization of appropriate teaching media has a positive effect on cognitive load. The application of cognitive load in the learning environment is mainly realized by utilizing appropriate teaching media. Liao et al. (2019) researched how teaching media affected learners’ cognitive load in a digital game-learning environment. The results show that teaching media reduces the extraneous cognitive load and the intrinsic cognitive load. Therefore, in the learning environment, researchers can appropriately use teaching media to reduce the cognitive load of learners to improve their performance level.

In terms of learning materials, presenting an appropriate amount of information has a positive impact on cognitive load. The application of cognitive load in learning materials is mainly realized by presenting an appropriate amount of visual information. Presenting too much visual information will overload the cognitive load of learners and reduce the efficiency of learning. Albus et al. (2021) designed a control experiment in the VR learning environment. Only one of the two experimental groups presented text annotation information. Comparing the grades of the two groups, researchers found that text annotation can promote germane cognitive load. Therefore, in the design of learning materials, an appropriate amount of information should be presented to learners.

From the three aspects of the application of cognitive load in education, the research of cognitive load mainly focuses on knowledge representation. It uses a variety of tools to improve the efficiency of knowledge representation and reduce the cognitive load of learners. Additionally, it has made contributions to promoting the development of education.

Problems in Cognitive Load Research

Various studies have shown (Akbulut et al., 2018; Demitriadou et al., 2020) that the presentation of knowledge in learning media will affect the cognitive load of individuals. Therefore, a large number of cognitive load studies focus on the presentation of knowledge by learning media, which is knowledge representation. However, the influence of specific learning behavior characteristics on cognitive load has been ignored. Scheiter et al. (2009) have explored the impact of learning behavior characteristics on cognitive load and learning results. They pointed out that learners with “more favorable learning behavior characteristics” reported less cognitive load and better grades. Unfortunately, their research did not point out what “more favorable learning behavior characteristics” specifically meant. They also
did not obtain any linear or non-linear relationship between specific learning behavior characteristics, grades, and cognitive load.

To sum up, although cognitive load has developed for 40 years, researchers have not conducted quantitative analysis on the cognitive load of online learners. Scheiter et al. (2009) proved that learning behavior characteristics can affect learners’ cognitive load in a hypermedia-learning environment. However, the question remains: “How do online learning behavior characteristics affect online learners’ cognitive load?” With the rapid development of online learning, it is necessary to explore the cognitive load of online learners so as to improve their overall performance level.

RESEARCH DESIGN

Data Source

Taking the course open dataset released by the Canvas Network platform (https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/1XORAL) as an example, the online learning behaviors are analyzed in the research. The dataset contains 325,200 pieces of data, with sufficient data volume. After data cleaning, a total of 921 valid data were obtained, which were used as research samples. Excel, SPSS, and Python were used for data processing and analysis in the research.

In the process of data cleaning, data with a completion rate of “one” are selected in Professions and Applied Sciences. Because “age_DI” reflect learners’ cognitive level or initial learning ability in a way. The “start_time_DI,” “last_event_DI,” “course_length,” and “ndays_act,” reflect learners’ learning time. The “nevents,” “nforum_posts,” and “nchapter,” reflect the degree of learners’ efforts. Therefore, eight kinds of learning behaviors include: “age_DI,” “ndays_act,” “nforum_posts,” “nevents,” “course_length,” “nchapter,” “start_time_DI,” and “last_event_DI,” and were selected as sample data in this research. The specific description is shown in Table 1.

Research Model

The primary task measurement method generally uses the method of measuring learning results to assess the cognitive load of human beings (Sweller, 2003). This indicates that there is a certain relationship between cognitive load and grade. Hsiao et al. (2019) pointed out that learners’ behavior characteristics will have a great impact on academic performance on online learning. Therefore,

<table>
<thead>
<tr>
<th>Column Name</th>
<th>Description</th>
<th>Attribute Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>start_time_DI</td>
<td>initial interaction time</td>
<td>The first interaction time of the user to be identified.</td>
</tr>
<tr>
<td>last_event_DI</td>
<td>last interaction time</td>
<td>The last interaction time of the user to be identified.</td>
</tr>
<tr>
<td>nevents</td>
<td>number of events</td>
<td>The number of interactions with the course. Recorded as page views.</td>
</tr>
<tr>
<td>ndays_act</td>
<td>learning event days</td>
<td>Total days of different events.</td>
</tr>
<tr>
<td>nforum_posts</td>
<td>posts</td>
<td>Total number of forum posts.</td>
</tr>
<tr>
<td>nchapter</td>
<td>number of learning chapters</td>
<td>Number of chapters interacting with learners.</td>
</tr>
<tr>
<td>course_length</td>
<td>course duration</td>
<td>The days of the course or the days of participants’ activities in the course, whichever is the greater.</td>
</tr>
<tr>
<td>age_DI</td>
<td>age</td>
<td>Age group to identify.</td>
</tr>
<tr>
<td>grade</td>
<td>academic record</td>
<td>Final grade of the course.</td>
</tr>
</tbody>
</table>
researchers can try to quantify the cognitive load by mining the behavior characteristics. Based on this, the research model was constructed as shown in Figure 1.

The multi-level data mining technology was used to analyze the learning behavior data. The research model was divided into four layers, and the result of each layer was used as input for the next layer.

**Main Learning Behavior Characteristic Extraction**

In the first layer, a single data mining technique (correlation analysis) was used to analyze the correlation between eight kinds of learning behaviors and grades. The purpose was to extract the learning behavior characteristics that had the strongest correlation with grades as the main learning behavior characteristics of the research.

**Clustering of Learners**

In the second layer, the same two data mining techniques (clustering analysis) were used to superimpose and enhance the accuracy of the analysis results. The main learning behavior characteristics obtained in the previous step and grades as the Y and X variables were used in this step for cluster analysis. After clustering, three categories of learners were obtained.

**Special Relationship Mining**

In the third layer, the three same data mining techniques (correlation analysis) were used for superposed analysis. By comparing the analysis results of the three kinds of learners, a special relationship was found that showed a correlation between grades and “nevents,” which was different in each type of learner.

**Quantitative Analysis of Cognitive Load**

In the fourth layer, the two techniques (regression analysis and boxplot analysis) were cross-superimposed twice to obtain the “critical value” that researchers were seeking. Based on the above analysis, the relationship between “nevents” and grades was further explored. The final results showed that the cognitive load of the online learners could be mapped by using “nevents.”

**DATA PROCESSING AND ANALYSIS**

**Main Learning Behavior Characteristic Extraction**

The Pearson correlation coefficient method was used to analyze the correlation between eight learning behaviors and grades. The results are shown in Table 2. It can be seen from the table that the eight
Learning behaviors are significantly correlated with the grades at the 0.01 level. This shows that learning time and effort will significantly affect the performance level of online learners. Among them, “nevents” and “ndays_act” have the strongest correlation with grades; the corresponding correlation coefficient is 0.621 and 0.681. The research results of Masui et al., (2014) show that learners’ activities and efforts are very important in higher education. The “nevents” and “ndays_act” can reflect online learners’ activities and efforts to a certain extent. This fully shows that there is a close correlation between online learners’ grades, “nevents,” and “ndays_act.”

Clustering Analysis of Learners

This clustering analysis was based on the extracted two main learning behavior characteristics “nevents” and “ndays_act.” To better understand the impact of learning behavior characteristics on different types of learners, the K-means clustering algorithm of unsupervised learning was conducted to the clustering analysis of online learning behavior.

The K-means clustering algorithm is easy to implement and fast to converge, which is the most widely used algorithm in cluster analysis. The basic idea is that for a dataset containing N data objects or tuples, the data is divided into several clustering groups or subgroups according to the given number of clusters K (K≤ N). After several iterations, the best clustering groups can be obtained. Based on this idea, two main learning behavior characteristics were used to conduct cluster analysis in this research.

K Value Selection

Before K-means clustering, researchers first must determine the K. Therefore, the “elbow rule” is used to select the K. A curve was constructed using the libraries of sklearn, Matplotlib, and pandas in Python. The visual results are shown in Figure 2.

The value of the cost function decreases rapidly with the increase of K in Figure 2, which reaches the inflection point when K = 3. After the point, the value of the cost function decreases slowly. Therefore, K = 3 was selected as the number of clustering groups in this research.

Cluster Analysis

After the K is determined, the KMeans function in the sklearn-cluster module is called by the researchers to conduct cluster analysis. The researchers set the number of cluster centers as three, the grades as the X variables, and the “nevents” and “ndays_act” as the corresponding Y variables. The clustering labels obtained from the experiment are described in the coordinate diagram in the form of points, and the results are shown in Figures 3 and 4.

Comparing Figure 3 with Figure 4, it was found that the clustering effect of using grades and “nevents” is better than grades and “ndays_act.” In Figure 3, the clustering results were hierarchical and obvious. Learners could be divided into three categories, named: Learner0, Learner1, and Learner2, respectively. It was observed that “nevents” of Learner0 were less than 200, and most

<table>
<thead>
<tr>
<th>Table 2. Correlation Analysis of Learning Behavior</th>
</tr>
</thead>
<tbody>
<tr>
<td>start_time_DI</td>
</tr>
<tr>
<td>Pearson Correlation</td>
</tr>
<tr>
<td>Sig. (Two-Tailed)</td>
</tr>
<tr>
<td>N</td>
</tr>
</tbody>
</table>

Note: ** At the 0.01 level (two tailed), the correlation is significant.
* At the 0.5 level (two tailed), the correlation is significant.
learners’ grades were a distributed range of 0–0.8. With Learner1 learners, the “nevents” were a distributed range of 180–391, and most learners’ grades were a distributed range 0.8–1. The “nevents” of Learner2 learners were over than 391, and the grades were a distributed range of 0.8–1. Although the classification of learners could be clearly observed in Figure 3, there were still many outliers.
Therefore, to more accurately describe learners’ learning characteristics, researchers needed to process and analyze the data again.

In Table 3, the number of outliers represents the number of learners in the corresponding category that do not match the distribution of grade. For example, among Learner0, most of the learners’ grades were a distributed range 0–0.8. However, there were 67 learners’ grades greater than or equal to 0.8, which were treated as outliers in the research. It can be seen from the table that Learner0 learners had the largest number of learners, but the lowest level of academic performance. Learner2 learners had the least number of learners, but the best academic performance. This showed that the overall academic performance level of online learners was low, and the effect of online learning needed to be improved. The learners with the worst academic performance also had the least “nevents.” The two types of learners with the best academic performance also had more “nevents” than the former. This showed that there was a certain correlation between the online learners’ grades and “nevents.” Learners with the lowest level of academic performance had the smallest learning timespan. Learners with the highest level of academic performance also had the largest learning timespan. This showed that there is a positive correlation between online learners’ grades and “ndays_act.” Due to the existence of outliers, the clustering effect was not the ideal state. Therefore, the dataset was analyzed and cleaned again in the research according to Table 3, wherein 785 pieces of data are obtained. According to the effect of the first clustering, grades and “nevents” were selected for clustering. The results are shown in Figure 5.

Comparing Figure 5 with Figure 3, the boundaries in learner clustering groups are clearer and more hierarchical in Figure 5. Although the clustering groups of Learner1 learners and Learner2

<table>
<thead>
<tr>
<th>Category</th>
<th>Number of Learners</th>
<th>Number of Outliers</th>
<th>Nevents Distribution</th>
<th>Ndays_Act Distribution</th>
<th>Grade Distribution</th>
</tr>
</thead>
<tbody>
<tr>
<td>Learner0</td>
<td>563</td>
<td>67</td>
<td>&lt;180</td>
<td>2~16</td>
<td>0~0.8</td>
</tr>
<tr>
<td>Learner1</td>
<td>272</td>
<td>69</td>
<td>180&lt;=&amp;&lt;391</td>
<td>2~25</td>
<td>0.8~1</td>
</tr>
<tr>
<td>Learner2</td>
<td>86</td>
<td>10</td>
<td>&gt;=391</td>
<td>2~32</td>
<td>0.8~1</td>
</tr>
</tbody>
</table>
Figure 5. Presentation of Clustering Results (Grades & “Nevents”)

![Presentation of Clustering Results](image)

learners are obvious, and the distribution range of grades is the same, the “nevents” are different. So, the questions in: “What is the correlation between online learners’ grades and ‘nevents’?”

**Correlation Analysis of “Nevents” and Grades**

Based on the abovementioned question, correlation analysis was carried out again in the research. The results are shown in Table 4.

Through the correlation analysis of the main learning behavior characteristics and grades, it is shown that although the grades of Learner2 learners and Learner1 learners are distributed in the same interval, the correlation between their grades and “nevents” are diametrically opposite. The grades of Learner1 learners were a positive correlation with “nevents,” and the grades of Learner2 learners were a negative correlation with “nevents.” In addition, in the first correlation analysis, grades were

<table>
<thead>
<tr>
<th>Learner0</th>
<th>nevents</th>
<th>ndays_act</th>
</tr>
</thead>
<tbody>
<tr>
<td>grade</td>
<td>Pearson correlation</td>
<td>.475**</td>
</tr>
<tr>
<td></td>
<td>Sig. (Two tailed)</td>
<td>.000</td>
</tr>
<tr>
<td></td>
<td>N</td>
<td>563</td>
</tr>
<tr>
<td>Learner1</td>
<td>nevents</td>
<td>ndays_act</td>
</tr>
<tr>
<td>grade</td>
<td>Pearson correlation</td>
<td>.249**</td>
</tr>
<tr>
<td></td>
<td>Sig. (Two tailed)</td>
<td>.000</td>
</tr>
<tr>
<td></td>
<td>N</td>
<td>272</td>
</tr>
<tr>
<td>Learner2</td>
<td>nevents</td>
<td>ndays_act</td>
</tr>
<tr>
<td>grade</td>
<td>Pearson correlation</td>
<td>-.218*</td>
</tr>
<tr>
<td></td>
<td>Sig. (Two tailed)</td>
<td>.044</td>
</tr>
<tr>
<td></td>
<td>N</td>
<td>86</td>
</tr>
</tbody>
</table>

Note: ** At the 0.01 level (two tailed), the correlation is significant.
* At the 0.5 level (two tailed), the correlation is significant.
also a positive correlation with “nevents.” The question to be answered was: “Why is the relationship between Learner2 learners’ grades and ‘nevents’ different from that of Learner1 learners?”

**Quantitative Analysis of Cognitive Load**

Regression analysis was used to further explore the relationship between grades and “nevents” of online learners in the research. The results are shown in Figure 6.

According to Figure 6, the relationship between grades and “nevents” is not a simple linear relationship, it’s a curved relationship that increases first and then decreases. Meister (James, 1977) found in his research that there was a curvilinear relationship between task demand and job performance, and task demand could be mapped to cognitive load. De Waard and Brookhuis (1996) also pointed out that task demand and task performance presented an “inverse U-curve” relationship. The relationship between “nevents” and grades in the research also conforms to this curve relationship, its grades rise first, and then decrease with the increase of “nevents.” This indicated that there was not only a simple linear relationship between grades and “nevents,” but also a complex curvilinear relationship. This was also the reason why Learner1 and Learner2 had the same grade distribution range, but the correlation between grades and “nevents” was different, because “nevents” of Learner1 did not exceed the peak of the “inverse U-curve,” while some “nevents” of Learner2 did exceed the peak of the “inverse U-curve.” Therefore, there was a negative correlation between “nevents” and grades of Learner2 learners. A specific example is shown in Figure 7.

In the research, the “inverse U-curve” relationship between the “nevents” and grades was consistent with the basic assumptions of primary task measurement. Therefore, “nevents” could also be mapped to the cognitive load of online learners. In the research, the “nevents” corresponding to the critical value of regression analysis was named the maximum cognitive load, and the corresponding grade was named the best learning performance. The online learners’ cognitive load could be quantified in this way. Multi-level data mining was used again to explore the maximum cognitive load of online learners in the research.

Boxplot can roughly detect the existence of outliers by drawing statistics that reflect the characteristics of data distribution, providing key information about the data location and dispersion. All “nevents” were detected through the boxplot in the research, and the results are shown in Figure 8. It is observed that there are a large number of “outliers” in “nevents,” which distribute on the right part of the vertex in the “inverse U-curve” graph. If all the outliers in the boxplot can be removed, the maximum observed value is the critical value in Figure 7.

Therefore, the “nevents” were reprocessed and re-conducted as a regression analysis in the research. The results are shown in Figure 9. There was a positive correlation between “nevents” and grades of Learner1 learners.
grades, so the grade will also improve with the increase of the “nevents.” Boxplot analysis was re-conducted based on the regression analysis results in Figure 9. The results are shown in Figure 10. There are no “outliers” in Figure 10. Therefore, the maximum observed value of boxplot is the value of the maximum “nevents” that online learners can bear. It is also the maximum cognitive load of online learners.

RESULTS

The analysis result of the main learning behavior characteristics is shown in Table 5. The maximum cognitive load of online learners was 424, and the best learning performance was 0.951. Therefore, learners can improve their grades by increasing the “nevents” when the “nevents” are less than 424 on online learning.

The proportion of age distribution in Learner1 and Learner2 at 34 and 35 and > = 55 was both higher than Learner0. Liang (1995) found that people’s cognitive level increased with age. Therefore,
the elder learners in the research had higher cognitive levels, which may also be one of the reasons why the average grade of Learner0 was lower than the latter two.

Learner0 had the lowest average grade and the largest difference from the best learning performance. They had the shortest learning time and the least “nevents,” which indicated that Learner
0 had fewer activities and efforts in the progress online learning. The average age of most Learner0 was between 19 and 34 years old, which indicated Learner0 had a lower cognitive level than Learner2.

Learner1 had a good grade, less the difference from the best learning performance. Learner1 spent more time on online learning; the difference between “nevents” and the largest “nevents” was small, and their ages were distributed between 19 and 34 years old. This showed that although Learner1 had a lower cognitive level than Learner2, they had put more time and effort into learning, so they had a good academic performance.

Learner2 learners had the best average grade, the longest learning time on online learning, and the most “nevents,” and the ages were distributed in the ranges of 19–34 and 34–55. However, the average “nevents” had exceeded the maximum cognitive load of learners. Therefore, among the Learner2 learners, the grade of some learners was lower than the best learning performance.

Therefore, in order to promote the learning performance of online learners, firstly, researchers can start from the perspective of increasing the learning activities of online learners. Secondly, researchers can start from the perspective of promoting learners’ efforts. Thirdly, it can also start from the perspective of reducing the cognitive load of online learners.

CONCLUSION

Accurate quantitative analysis is one of the advantages of data mining and one of the key reasons why data mining can promote personalized online learning. In this study, the data mining technology was superimposed and the online learning behavior data was analyzed in layers. In the process of data mining and analyzing, a relationship between cognitive load and online learning behavior characteristics was found. Therefore, the grade was used as an intermediary object to map the specific online learning behavior characteristic to the cognitive load of online learners.

With the rapid development of massive online learning, the problem of learners’ cognitive overload has become a huge obstacle to the development of personalized online learning. According to the research of Eppler and Mengis (2008), it can be inferred that the input of a large amount of information on online learning will cause an unnecessary cognitive load on learners. Analyzing and mining massive learning behavior data to identify the factors that affect the cognitive load of online learners has become an important channel to exploring their cognitive load and an important way to achieve personalized online learning. However, at present, the research on the cognitive load of online learners does not receive enough attention. The effect of “nevents” on the cognitive load of online learners also has not received enough attention. Therefore, this research study research was conducted as a preliminary exploration to fill the gap in the research of cognitive load of online learners.

The research shows that is an “inverse U-curve” relationship between “nevents” and grades. At the same time, the research also shows that there is a close relationship between learners’ grades and their competence level. Thus, in future research, researchers will be able to use quantitative analysis and predict the competence of online learners.

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Lingyan Liu is a master’s student from the School of Information Science and Technology, Yunnan Normal University. Her research interests include learning analytics, machine learning, digital learning environments, and technologies.

Bo Zhao, corresponding author, is a professor and doctoral supervisor from Key Laboratory of Educational Information for Nationalities, Ministry of Education and School of Information Science and Technology, Yunnan Normal University. From September 2005 to July 2006, she worked as a visiting scholar in the Knowledge Engineering Laboratory, School of Computer Science and Technology, Tsinghua University. From September 2011 to September 2012, she worked as a visiting scholar in the School of Education, Ohio State University, Columbus, USA, and participated in the research project of tutor’s educational evaluation. Her research interests include Knowledge Engineering and intelligent teaching systems.

Yiqiang Rao is a master’s student from Key Laboratory of Educational Information for Nationalities, Ministry of Education, Yunnan Normal University. His research interests include ethnic education and Informationization.