Summer 7-26-2022

The Influence of Students' Online Silent and Active Participation on Learning Performance and Experience

Li Chen
College of Management, Shenzhen University, Shenzhen, 518000, China

Chen Zou
College of Management, Shenzhen University, Shenzhen, 518000, China

Shuang Geng
College of Management, Shenzhen University, Shenzhen, 518000, China, gs@szu.edu.cn

Zhao Du
Business School of Sport, Beijing Sport University, Beijing, 100000, China

Full Research Paper

The Influence of Students' Online Silent and Active Participation on Learning Performance and Experience

Li Chen[1], Chen Zou[1], Shuang Geng[1], Zhao Du[2]*

[1] College of Management, Shenzhen University, Shenzhen, 518000, China

[2] Business School of Sport, Beijing Sport University, Beijing, 100000, China

Abstract: The number of online learning users grows drastically and analyzing their learning behaviour has become a hot spot in recent years. However, there have been limited comparative studies on different learning processes, i.e. silent learning and active learning behaviour, and their influence on learning performance and learning experience. This study distinguishes between two types of learning behaviour, that is, silent learning which corresponds to content consumption, and active participation which corresponds to content contribution. By collecting and analyzing user log data from a Massive Online Open Course using OLS regression and sentiment analysis, we find that students' reply, video watching, and test taking activities simultaneously enhance their learning performance and course learning experience. By contrast, comment behaviour does not indicate better student performance and learning experience. These findings provide novel insights in student silent and active participation, and point to future investigation of predictive studies based on real-time learning behaviour.

Keywords: Silent learning, active learning, learning performance, learning experience

1. INTRODUCTION

In recent years, with the continuous progress of science and technology, online education has been developing rapidly. However, due to the lack of direct supervision, it is difficult for teachers to know students' mastery of course knowledge and to provide corresponding help and intervention in time [1]. Since the number of online learning users has increased drastically, a large number of user learning behaviour data has been accumulated on the online learning platforms, which is very important to understand learners' learning progress and it can help to predict learning outcomes [2].

Online learning behaviour can be considered as the way learners participant in online learning, which is shaped by the influence of learners' subjective thinking as well as learning environment [1]. This paper distinguishes between two types of online learning behaviour, namely, silent learning and active learning behaviour according to the level of user participation (i.e. content consumption and content contribution). Content consumption behaviour such as watching learning videos and taking online tests is considered as silent learning behaviour. By contrast, content contribution such as posting, replying, as well as commenting is recognized to as active learning behaviour [3][4]. Both of these two types of behaviour are vital to learning outcomes [5].

Learning performance is considered as the most vital cognitive variable to reflect course learning outcomes, while learning experience is seen as the most important emotional variable [6]. Previous studies mainly used self-reported questionnaires to investigate the relationship between students' learning behaviour and learning outcomes [6][7]. However, recently, there is an emerge of studies that use user behavioural data, such as system log data and user discourse, to investigate the learning process and learning outcomes, which is more objective [8][9]. For example, several studies utilizing LMS (learning management system) data have shown that participation indicators and patterns are strongly correlated with academic achievement [9]. Accordingly, in this study, we use

* Corresponding author. Email: gs@szu.edu.cn

the log data from backstage to test the effects of silent and active students' online learning behaviour on learning performance and experience.

This research makes several contributions. First, it classifies online learning behaviour into two categories (silent learning and active learning behaviour) from the perspective of user participation, which helps to understand the conception of online learning behaviour. Second, it integrated sentiment analysis into empirical study, which provides evidence for effectively utilizing learner discourse data. This research also provides important practical implications for both teachers, learners and teaching platforms.

2. THEORETICAL FOUNDATIONS

Online learning behaviour is a train of activities that learners take in the online learning process, such as watching learning videos, browsing forums, viewing courseware, communicating and discussing with others and so on [1]. Different scholars have different classifications of online learning behaviour. For example, Wang put forward that online learning behaviour are a serial of chronological behaviour, such as, problem-solving, online study, social interaction, self-assessment and self-reflection [9]; Ning & Oliver proposed that online learning behaviour can be divided into four categories: trajectory behaviour, social behaviour, resource learning behaviour, evaluation and reflection behaviour [1].

Since learning behaviour prediction is a vital part in online education field [1], many researchers have done some explorations. For example, Dietzuhler & Hurn proposed that analyzing learners' learning behaviour can predict their learning performance, which can help teachers improve the teaching quality and course design [10]; Qiu et al., developed a unified predictive model to predict learners' certificate acquisition and academic performance by analyzing learners' learning behaviour [11]; Sorour & Mine used random forests and predictive trees in machine learning to predict learner performance based on learning behaviour [12].

Online learning behaviour can be considered as the way users participate in online learning, which is shaped by the influence of learners' subjective thinking as well as learning environment [1]. For example, when it comes to learners' subjective thinking, online learners can choose whether or not to watch all the learning videos to acquire knowledge. And they can also choose whether or not to discuss with others about his or her learning process. When it comes to learning environment, curriculum design, layout of online learning platform may also guide the formation of learners' learning behaviour.

This paper identifies two types of learning behaviour including silent learning and active learning behaviour from the perspective of user participation. To be more specific, silent learning behaviour corresponds to content consumption, whereas active learning behaviour corresponds to content contribution [3][4]. Content consumption through watching learning videos and taking tests is invisible by others. However, previous research indicates that although silent learning behaviour contributes to online learners' performance, students need to spend a large amount of time on these activities to be successful silent learners, such as reading learning resources [5]. Content contribution is publicly visible and it mainly occurs in the forum via posting, replying, and commenting, which adds to substantive discussions and have positive effects on user participation [3][4]. Previous studies have implied that silent learning behaviour helps learners become more focused, while active learning behaviour helps them to absorb knowledge effectively [13]. Therefore, these two types of learning behaviour are very important for learners to get good learning outcomes.

3. THE RESEARCH MODEL AND HYPOTHESES

3.1 Research model

In this paper, we divide online learning behaviour into silent learning behaviour and active learning behaviour from the perspective of user participation, and further investigate their impacts on learning outcomes using system log data. Learning outcomes not only refer to learning performance, but also include learners' attitude toward the learning experience, which is reflected by their comments. Figure 1 presents our overall conceptual model. The deduction of each hypothesis is as follows.

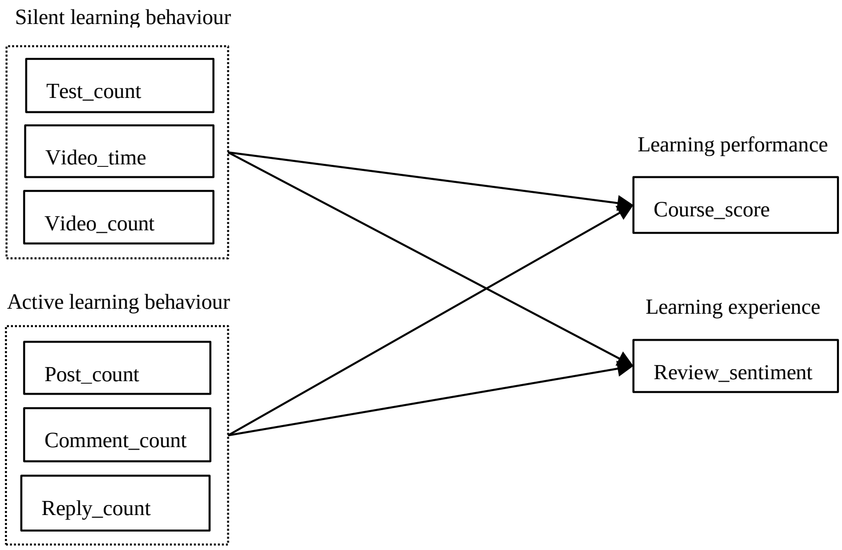

Figure 1. The research model

3.2 Impacts of silent learning behaviour on learning outcomes

In the online learning context, learners' self-regulated learning is more important than that on the face-to-face offline courses. Because they should arrange their study processes on their own, and without the direct supervision of teachers [7]. As we mentioned above, silent learning behaviour corresponds to content consumption such as watching learning videos and taking tests [3][14], which can indicate their learning engagement, and further predict their learning outcomes [2].

Learning performance and learning experience are the most vital variables to reflect course outcomes, respectively representing the cognitive and emotional dimensions. Course score is intuitively used to indicate students' learning performance [7], while course satisfaction is widely used to reflect one's learning experience [15]. Besides, silent learning behavior can be regarded as the interaction between users and contents [16], which can largely explain to what extent students are satisfied with the course. Based on the discussion above, we propose that:

H1: Silent learning behaviour may be positively associated with learning performance.

H1a: Test_count may be positively associated with learning performance.

H1b: Video_time may be positively associated with learning performance.

H1c: Video_count may be positively associated with learning performance.

H2: Silent learning behaviour may be positively associated with learning experience.

H2a: Test_count may be positively associated with learning experience.

H2b: Video_time may be positively associated with learning experience.

H2c: Video_count may be positively associated with learning experience.

3.3 Impacts on active learning behaviour on learning outcomes

Forum participation is a very important part during learning processes [6]. In the context of online learning, active learning behaviour corresponds to content contribution [3][4], which mainly happens in the discussion forum. Active learning behaviour can be seen as communicating with teachers and peers to learn from each other or exchange ideas via posting, replying, and commenting [14]. For example, learners could post their questions in the forum and waiting for others' reply, by which they can solve problems met in the silent learning processes which cannot be solved by themselves [9]. It can help learners complete their course learning and improve their learning efficiency, which contributes to the learning outcomes. As it mentioned above, learning performance and learning experience are the most vital factors to reflect learning outcomes. That is to say, the more frequent interaction with teachers or other learners, the better learning performance and experience they will get [6]. Therefore, we propose the following:

H3: Active learning behaviour may be positively associated with learning performance.

H3a: Post_count may be positively associated with learning performance.

H3b: Comment_count may be positively associated with learning performance.

H3c: Reply_count may be positively associated with learning performance.

H4: Active learning behaviour may be positively associated with learning experience.

H4a: Post_count may be positively associated with learning experience.

H4b: Comment_count may be positively associated with learning experience.

H4c: Reply_count may be positively associated with learning experience.

4. METHOD

4.1 Data collection

To investigate the proposed hypotheses, student behavioural data was collected from one of the largest online course providers in China. Student learning records were extracted from a course "Nutriology", which is a stable course opened for 11 semesters continuously with more than 10 thousand play count. In order to ensure users' learning contexts are similar, we only selected users' log data for the semester from January 29, 2020 to May 27, 2020 for our research. Because during this stage (COVID-19 period), almost all students need to attend classes online. After cleaning the data set by removing missing and abnormal samples, and matching the process records with student learning performance records, 345 data samples were obtained for further analysis. The data set was collected only for academic research, and the personal information of none of the learners was identified and stored.

4.2 Variable measurement

On the basis of student learning record data, we divided the behavioural features into silent learning behaviour and active learning behaviour. The features for measuring silent learning behaviour include the number of tests taken, the time of video watching, and the number of videos watching [14]. And the features for measuring active learning behaviour include the number of posts, number of replies, and comments on others' posts at the course discussion forum [6]. The student course score was used to represent his/her learning performance [7].

Student learning experience was evaluated through students' course reviews which reflect their perceptions and opinions [17]. Thus, we employed an open-source sentiment classification system established by Baidu based on the Bi-LSTM model to obtain the sentiment polarity of reviews [18]. The Bi-LSTM is a type of recurrent neural network model that accepts the input of the review sentence and outputs three results: sentiment polarity (0 represents negative, 1 represents positive), probabilities for positive sentiment (range from 0 to 1) and probabilities for negative sentiment (range from 0 to 1) [8].

Learners' gender and member type were treated as control variables and coded as dummy variables. Details about the variables are reported in Table 1. Table 2 presents the descriptive statistics about variables. Table 3 reported the pair-wise correlations of the main variables in the research model, which preliminarily proves the relevance of learning behaviour and learning outcomes.

Table 1. Details of study variables

Variable	Measurement items	Explanation
Silent learning behaviour	Test_count	the number of tests performed
	Video_time	the time spent on watching learning videos
	Video_count	the number of learning videos watched
Active learning behaviour	Post_count	the number of posts
	Comment_count	the number of comments
	Reply_count	the number of replies
Learning performance	Course_score	the final score of this course
Learning experience	Review_sentiment	the positive emotion score of the review
Gender	Gender	dummy coded as male = 1; female = 2.
Member_type	Member_type	dummy coded as student = 1; on the job = 2; others = 3.

Table 2. Descriptive statistics

Variable	Mean	Sd	Min	Max
Course_score	55.06	30.67	1	99.18
Review_sentiment	0.786	0.307	0.00830	0.998
Post_count	0.377	1.030	0	9
Test_count	24.33	11.81	1	66
Comment_count	0.365	1.325	0	13
Video_time	4,678	5,106	2	49,651
Video_count	16.36	12.40	1	40
Reply_count	9.304	8.522	1	56
Gender	1.646	0.479	/	/
Member_type	1.493	0.615	/	/

Table 3. Pair-wise correlations

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1) Coures_score	1									
(2) Gender	0.058	1								
(3) Member_type	-0.105*	-0.107 **	1							
(4) Post_count	0.122 **	0.018	0.151 ***	1						
(5) Test_count	0.768 ***	0.023	-0.027	0.261 ***	1					
(6) Reply_count	0.614 ***	0.064	-0.131 **	0.231 ***	0.429 ***	1				
(7) Comment_count	0.134 **	0.007	0.064	0.395 ***	0.195 ***	0.185 ***	1			
(8) Video_time	0.162 ***	-0.023	-0.043	0.008	0.190 ***	0.033	0.008	1		
(9) Video_count	0.264 ***	-0.006	0.039	-0.026	0.248 ***	0.065	-0.015	0.690 ***	1	
(10) Review_sentiment	0.366 ***	0.173 ***	-0.073	0.057	0.332 ***	0.278 ***	0.087	0.114 **	0.202 ***	1

*Note. * P < 0.1; ** P< 0.05; *** P< 0.01; n.s. = not significant*

OLS regression analysis was performed for investigation of direct impacts of silent learning and active learning behaviour. We presumed that the measurement variables of learning performance and learning experience are normally distributed. In the OLS regression analysis, the main effects include the direct impacts of silent learning and active learning behaviour on students' learning performance and learning experience. The users' gender and member type are set as control variables. The OLS regression models are as follows:

Equation (1): *learning performance i =α0 +β1 test_count i +β2 video_count i +β3 video_time i +β4 post_count i +β5 comment_count i +β6 reply_count i +βj control_variables ij +εi*

Equation (2): *learning experience i =α0 +β1 test_count i +β2 video_count i +β3 video_time i +β4 post_count i +β5 comment_count i +β6 reply_count i +βj control_variables ij +εi*

Where *β1, β2, …, β6* are parameter estimates for the hypothesized effects, *α0* is the intercept, *εi* is a normally distributed error term, and *βj* is the parameter estimate for the jth control variable. The parameter estimates have a straightforward interpretation: a one-unit change in measures of the predictor variables will be associated with *β1, β2, …, βj* unit change in outcome variables, respectively.

4.3 Results

Results of the model estimation are reported in Table 4. For equation (1), control variables, silent learning behaviour and active learning behaviour explain 71.3% of the variance in learning performance, 2%, 36%, 33.3%, respectively. For equation (2), control variables, silent learning behaviour and active learning behaviour explain 18.1% of the variance in learning experience, 3.3%, 7.1%, 7.7%, respectively. Multi-collinearity was not an issue in the models, because the variance inflation factor (VIF) for the independent variables ranged between 1.02 and 2.03, which are below the threshold of 10.

Table 4. Summary of OLS regression estimation

Variables	Learning performance			Learning experience		
	Model (1)	Model (2)	Model (3)	Model (1)	Model (2)	Model (3)
	Coefficient (S.E.)	Coefficient (S.E.)	Coefficient (S.E.)	Coefficient (S.E.)	Coefficient (S.E.)	Coefficient (S.E.)
Gender 2 (female)	3.250 (0.94)	1.149 (0.42)	1.136 (0.60)	0.108*** (3.12)	0.098*** (2.95)	0.098*** (3.06)
Member_type 2 (on the job)	-8.400** (-2.41)	-2.340 (-0.82)	-0.717 (-0.36)	-0.031 (-0.89)	-0.003 (-0.10)	-0.002 (-0.07)
Member_type 3 (others)	-3.349 (-0.49)	0.337 (0.06)	-3.989 (-1.04)	-0.049 (-0.72)	-0.037 (-0.55)	-0.061 (-0.93)
Post_count		-0.802 (-0.56)	-3.448*** (-3.47)		-0.007 (-0.39)	-0.015 (-0.88)
Reply_count		2.190*** (13.49)	1.313*** (10.96)		0.009*** (4.84)	0.006*** (2.85)
Comment_count		0.689 (0.63)	-0.091 (-0.12)		0.011 (0.87)	0.009 (0.70)
Test_count			1.618*** (18.15)			0.006*** (4.06)
Video_count			0.283*** (2.75)			0.004** (2.34)
Video_time			-0.000 (-1.10)			-0.000 (-0.64)
Constant	56.239*** (17.56)	34.825*** (11.68)	1.211 (0.45)	0.730*** (22.92)	0.636*** (17.70)	0.471*** (10.28)
Observations	345	345	345	345	345	345
R-squared	0.020	0.380	0.713	0.033	0.104	0.181
F	2.323	34.54	92.63	3.888	6.547	8.199

*Note. * P < 0.1; ** P< 0.05; *** P< 0.01; n.s. = not significant*

Main effects: In equation (1), test_count ($\beta1 = 1.618$, $p < 0.01$), video_count ($\beta2 = 0.283$, $p < 0.01$) and reply_count ($\beta6 = 2.190$, $p < 0.01$) are positively associated with learning performance, indicating that H1a, H1c and H3c are supported. However, comment_count ($\beta5 = 0.689$, $p > 0.1$) is not significantly associated with learning performance, that is to say, H3b is not supported. Besides, video_time ($\beta3 = 0.000$, $p > 0.1$) and post_count ($\beta4 = -0.802$, $p > 0.1$) have no statistically significant association with learning performance, implying that H1b, H3a are not supported. In equation (2), test_count ($\beta1 = 0.006$, $p < 0.01$), video_count ($\beta2 = 0.004$, $p < 0.05$) and reply_count ($\beta6 = 0.009$, $p < 0.01$) are positively associated with learning experience, indicating that H2a, H2c and H4c are supported. Conversely, video_time ($\beta3 = -0.000$, $p > 0.1$), post_count ($\beta4 = -0.007$, $p > 0.1$) and comment_count ($\beta5 = 0.011$, $p > 0.1$) are found have no statistically significant association with learning experience. Therefore, H2b, H4a and H4b are not supported.

Control effects: For the control variable of gender, we used male (gender1) gender as baseline variable and coded it as 1, and the female (gender2) was coded as 2. Therefore, the results represent the significance of effect of female gender in compared with male gender. we only found a positive association between female users and learning experience ($\beta = 0.098$, $p < 0.01$), which suggests that female users have better online learning experience than male users. Similarly, regarding member type, we used student (member_type1) member type as baseline variable and coded it as 1, and those on the job (member_type2) and other (member_type3) member types were separately coded as 2 and 3. we found that all dummies are not statistically significant, indicating that users' learning performance and learning experience don't vary too much between different member types. Table 5 summarized the results of the hypotheses-testing in study 1.

Table 5. Summary of Hypotheses Testing

Hypotheses	Results
H1a: Test_count may be positively associated with learning performance.	Supported
H1b: Video_time may be positively associated with learning performance.	Not supported
H1c: Video_count may be positively associated with learning performance.	Supported
H2a: Test_count may be positively associated with learning experience.	Supported
H2b: Video_time may be positively associated with learning experience.	Not supported
H2c: Video_count may be positively associated with learning experience.	Supported
H3a: Post_count may be positively associated with learning performance.	Not supported
H3b: Comment_count may be positively associated with learning performance.	Not supported
H3c: Reply_count may be positively associated with learning performance.	Supported
H4a: Post_count may be positively associated with learning experience.	Not supported
H4b: Comment_count may be positively associated with learning experience.	Not supported
H4c: Reply_count may be positively associated with learning experience.	Supported

4.4 Robustness check

We examined the robustness of our results using an alternative measure of learning experience. To be more specific, we employed TextMind, a Chinese language psychological analysis system based on SC-LIWC dictionary to identity the words related to positive emotion process (e.g., good, nice) to indicate users learning experience based on their course comments [19]. Our results did not change in any significant way after we reran our models, which indicates our results are robust.

4.5 Supplementary experiment

We conducted a supplementary experiment to convince our results using a questionnaire data collected from students with Small Private Online Course (SPOC) learning experience during the COVID-19 stage to ensure the taking-class context is similar. We totally received 157 valid responses and most of them are from universities in Guangdong province of China (females = 94, males = 63). The data was analyzed by SmartPLS software, and table 6 shows the results, from which we find that both silent learning and active learning behaviour have significant impacts on learning outcomes, suggesting that our results are stable.

Table 6. The direct path effects

Path	Path coefficient	T statistics
Silent learning behaviour -> learning performance	0.206*	1.984
Silent earning behaviour -> learning experience	0.278***	3.375
Active learning behaviour -> learning performance	0.265**	2.996
Active learning behaviour -> learning experience	0.352***	3.871

*Note. * P < 0.05; ** P< 0.01; *** P< 0.001 ；n.s. = not significant*

5. DISCUSSION

5.1 Impacts of silent learning behaviour on learning outcomes

Our results confirmed that most of silent learning behaviour will influence learning outcomes. Learners who take more tests before final exam can examine their mastery of learning, so as to find out omissions as well as make up for deficiencies and further obtain better learning outcomes. Previous researches show that learning videos are key components to master knowledge [20]. Therefore, the more learning videos learners watch, the more comprehensive knowledge they will obtain and they will get better learning outcomes. However, the time of watching videos has no significant impact on the learning performance and learning experience. This can be interpreted as those learners have been playing some certain videos, which means that they only grasp a part of knowledge. Besides, those learners with good learning outcomes may playing learning videos at double speed [20], leading to shorter watching video time. This highlights the importance of efficiency of silent learning.

5.2 Active learning behaviour impact learning outcomes

Compared with silent learning behaviour, active learning behaviour is relatively less important. It shows that in order to obtain good learning outcomes, the most important thing is personal efforts such as viewing more learning resources [5]. Active learning behaviour via communicating with teachers and peers only plays an auxiliary role. In this study, active learning behaviour includes the number of posts, replies and comments. Among them, the number of replies has a significant impact on learning outcomes, indicating that learners' attention to other people's problems and active participation in discussion can promote their own understanding and digestion of knowledge points [14], which helps promote learning outcomes. However, the number of comments has no significant impact on learning outcomes. In fact, we discover that the number of comments is quite few for both silent and active learners, which may be due the features of learning platform or users' unwillingness to comment. According to our results, less comments does not means less learning motivation and will not lead to worse learning outcomes. To our surprise, post_count is negatively related to learning performance, while it has no significant effect on learning experience. This may be because that when users encounter problems, they will post for help without their independent thinking and thus accumulated a lot of posts, which is not conducive to the mastery of knowledge.

5.3 Contributions

The theoretical contribution of this study is as follows. First, it classifies online learning behaviour into silent learning behaviour and active learning behaviour from the perspective of learner participation, which helps to understand the conception of online learning behaviour [6]. Second, we integrated the sentiment analysis into the empirical study, which provides evidence for effectively utilizing learner discourse data.

This research has some practical implications for both teachers, learners and teaching platforms. First, the results show that test_count, video_count, and reply_count significantly impact both learning performance and learning experience. From the perspective of teachers, they can design tests with small number of questions and higher frequency, and release tests in time after class, so as to help students review in time, check omissions and fill vacancies. From the perspective of students, if they want to obtain good learning outcomes, they are supposed to do more tests and watch more learning videos so as to master knowledge. Besides, they can also take part in the online learning discussion to exchange ideas and knowledge. Finally, for learning platforms, they should continuously optimize the structure of learning platforms, so as to make it easier for students to obtain learning resources, and make the communication between students and teachers more flexible.

5.4 Limitations and future research

There are several limitations in this study. First, due the limitation of our data collection, we cannot supplement student historical learning performance to control the intrinsic learning motivation of the sample learners. Therefore, future study can try to include more variables and student historical performance in the analysis. Second, due to the availability of data, we only used log data from one course to test our hypothesis, more subjects can be included in the future.

6. CONCLUSION

This paper first distinguishes between two types of online learning behaviour, namely silent learning and active learning behaviour and explores their impacts on learning performance and learning experience. Sentiment analysis method is used for extracting student learning behaviour features, and OLS regression analysis is applied for model construction. Results imply that most of silent learning behaviour (test_count, video_count) and relatively few active learning behaviour (reply_count) have positive impacts on student learning outcomes. These findings suggest that contrast to active learning behaviour, silent learning behaviour plays more important role for students to get better learning outcomes. Therefore, both teachers, learning platforms and learners themselves should focus more on silent learning behaviour, so as to obtain better learning outcomes. There are several limitations in this study that will guide our future research. In this paper, we used review sentiment for measurement of student learning experience. Alternative indicators can be also considered when more user features are available.

ACKNOWLEDGEMENT

This work is supported by grants from National Natural Science Foundation of China [71901150]; Shenzhen Higher Education Support Plan [20200826144104001]; Guangdong Province Innovation Team "Intelligent Management and Interdisciplinary Innovation" (2021WCXTD002); Shenzhen University Educational Research Project [JG2020119].

REFERENCES

[1] Ning Y, Oliver T. (2019). Online learning behaviour analysis based on machine learning. Asian Association of Open Universities Journal, 14(2): 97-106.

[2] Chen W, Brinton C G, Cao D, Mason-Singh A, Lu C, Chiang M. (2019). Early detection prediction of learning outcomes in online short-courses via learning behaviour. Learning Technologies, IEEE Transactions on, 12(1): 44-58.

[3] Phang C W, Kankanhalli A, Tan B C Y. (2015).What motivates contributors vs. lurkers? An investigation of online feedback forums. Information Systems Research, 26(4): 773-792.

[4] Malinen S. (2015). Understanding user participation in online communities: A systematic literature review of empirical studies. Computers in human behavior, 46: 228-238.

[5] Shukor N A, Tasir Z, Henny V. (2015). An examination of online learning effectiveness using data mining. Procedia - Social and behavioural Sciences, 172(1): 555-562.

[6] Oyelere S S, Olaleye S A, Balogun O S, Tomczyk U. (2021). Do teamwork experience and self-regulated learning

determine the performance of students in an online educational technology course? Education and Information Technologies, 26: 1-25.

[7] Im T, Kang M. (2019). Structural relationships of factors which impact on learner achievement in online learning environment. International Review of Research in Open and Distance Learning, 20(1): 112-124.

[8] Geng S, Niu B, Feng Y, Huang M. (2020). Understanding the focal points and sentiment of learners in mooc reviews: a machine learning and sc‐liwc‐based approach. British Journal of Educational Technology, 51(5): 1785-1803.

[9] Wang F H. (2017). An exploration of online behaviour engagement and achievement in flipped classroom supported by learning management system. Computers & Education, 114(nov.): 79-91.

[10] Dietzuhler B, Hurn J. (2013). Using learning analytics to predict (and improve) student success: a faculty perspective. Journal of Interactive Online Learning, 12 (2): 17-26.

[11] Qiu J, Tang J, Liu TX, Gong J, Zhang C, Zhang Q, Xue Y. (2016). Modeling and predicting learning behaviour in MOOCs. Proceedings of the Ninth ACM International Conference on Web Search and Data Mining. New York: Association for Computing Machinery, 93-102.

[12] Sorour S E, Mine T. (2016). Building an interpretable model of predicting student performance using comment data mining. The 5th IIAI International Congress on Advanced Applied Informatics (IIAI-AAI), IEEE, 285-291.

[13] Stoeffler K, Rosen Y, Bolsinova M, Davier A. (2019). Gamified performance assessment of collaborative problem-solving skills. Computers in Human behaviour, 104 (Mar.).

[14] Wang F H. (2019). On the relationships between behaviour and achievement in technology-mediated flipped classrooms: a two-phase online behavioural pls-sem model. Computers & education, 142(Dec.): 1-12.

[15] Hamdan K M, Al-Bashaireh A M, Zahran Z, Al-Daghestani A, Shaheen A M. (2021). University students' interaction, internet self-efficacy, self-regulation and satisfaction with online education during pandemic crises of covid-19 (sars-cov-2). International Journal of Educational Management, 35(3): 713-725.

[16] Kuo Y C, Walker A E, Schroder K, Belland B R. (2014). Interaction, internet self-efficacy, and self-regulated learning as predictors of student satisfaction in online education courses. Internet & Higher Education, 20(jan.): 35-50.

[17] Shah M, Pabel A, Martin-Sardesai A. (2019). Assessing google reviews to monitor student experience. International Journal of Educational Management, 34(3): 610-625.

[18] Tian H, Gao C, Xiao X, Liu H, He B, Wu H, et al. (2020). Skep: sentiment knowledge enhanced pre-training for sentiment analysis. Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics. In: Dan Jurafsky, Joyce Chai, Natalie Schluter, Joel Tetreault, eds. Association for Computational Linguistics, 4067-4076.

[19] Gao R, Hao B, Li H, Gao Y, Zhu T. (2013). Developing simplified Chinese psychological linguistic analysis dictionary for microblog. International conference on brain and health informatics. In: Elisa Bertino, Wen Gao, Bernhard Steffen, Gerhard Woeginger, Moti Yung, eds. Lecture Notes in Computer Science, 359–368.

[20] Brame C J. (2016). Effective educational videos: principles and guidelines for maximizing student learning from video content. CBE life sciences education, 15(4): es6-es6.