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Investigating Online Behavioral Learning Engagement and Performance based on LMS Data amid COVID-19: Does Gender Really Matter?

Chenjuan Jiang[a,*], Dandan Liu[b]

School of Foreign Studies, Jiangnan University, Wuxi, 214122, China
[a]lindajcj@163.com, [b]443614849@qq.com
[*]Corresponding author

Abstract: *Learning management systems (LMSs) have been widely used in Chinese higher education institutions. This study investigated student learning engagement of English as a foreign language (EFL) on an LMS among 109 Chinese undergraduates and the relationship between online learning behavioral engagement and learning outcome. The results showed that most students devoted themselves to epidemic-induced online EFL learning and achieved desirable learning performance. But they have encountered a few challenges. Regression analysis showed that student engagement data on the LMS can predict their learning outcomes. Student participation in interactive activities can predict 18.6% of the variance in students' final test scores. T-test analysis of variances revealed that female students showed higher online learning engagement and performance than their male counterparts. Moreover, the correlation between online behavioral engagement and the learning outcome is stronger in female students than that in male students. Educational implications, limitations, and directions for future research are discussed.*

Keywords: *Online Behavioral Learning Engagement; Learning Performance; Gender; LMS Data*

1. Introduction

Due to the spread of the coronavirus Omicron variant in the spring of 2022, many universities in China switched to online teaching again. Since online teaching plays such an important role during the crisis and there is a tendency that with the development of technology, online teaching has been widely spread all over the world, it calls for more research on this teaching mode, especially the learning performance in the online learning process. Learning engagement is critical to the success of any educational process, including language learning [1]. Although there are studies pertinent to students' learning engagement and learning outcomes of online learning, most of these studies generally used self-reported questionnaires to measure the level of learning engagement, which raises concerns regarding whether self-reported data can validly represent actual learning behaviors in the authentic learning environment [2]. Another measure of student engagement is the observational method, but the limitation of the face-to-face observational measure of student engagement occurs when students are in different locations when online learning is implemented during the epidemic. In the past decades, learning management systems (LMSs) have been an efficient tool to track student behavioral data through log files and provided new opportunities for exploring students' learning engagement and performance. However, only very few studies have used data taken from digital LMSs to explore student engagement and learning outcomes, let alone studies on EFL courses.

Given that students' learning behaviors are automatically recorded in the LMSs, which have been very popular in many Chinese higher education institutions, this study aims to empirically examine the status of Chinese undergraduate students' online behavioral learning engagement in an EFL course on the LMS MosoTeach (hereafter MT) as well as the relationship between students' behavioral learning engagement data generated by MT and their learning outcomes. As gender is an important student factor that is relevant to student engagement and performance [3], this study also explores gender differences in all the variances and whether gender affects the relationship between student engagement and online learning performance.

Findings from this study will contribute to a better understanding of the characteristics of student activities in the fully online course, which is significant for instructors in similar settings to adjust

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instructional strategies to improve students' learning performance and the quality of the course.

2. Literature review

2.1 Learning engagement

Student engagement usually refers to the time and effort that students devote to their academic experiences [4]. Education researchers have long maintained that learner engagement is one of the major factors that influence learning outcomes [5]. The nature and structure of learning engagement have been studied by many researchers. Learning engagement has been defined in many ways, among which Fredricks' three components definition is the most popular and widely accepted one. According to Fredricks, the three types of engagement include behavioral engagement, emotional engagement, and cognitive engagement. Behavioral engagement refers to involvement in learning and academic tasks, the central aspect of which is participation. Emotional engagement concerns students' affective reactions in the classroom. Cognitive engagement is defined in terms of being strategic or self-regulating [6]. Since no research can examine all three aspects of learning engagement thoroughly, it is important for each researcher to conduct the study with their own focus on one or two particular sub-struct of learning engagement. Therefore, although all three dimensions of engagement are shown to have positive relations to student learning, the current study specifically focuses on behavioral engagement because students' activity participation data on LMS is the reflection of their learning behavior. We define behavioral learning engagement as students' involvement in learning activities with effort, persistence, and concentration [7], which can be observed via indicators such as the quiz scores they got, the time span they watched the video resources and the frequency they accessed the non-video resources in the LMS.

With engagement being a growing topic of interest in technology-enhanced learning, students' engagement with the online courses and identification of their engagement characteristics are attracting increasing attention in the online learning context. Online learning provides students with the chance to get information and resources at their own pace in any place. Students can obtain support from their instructors and fellow students in the online learning community, which helps them get engaged in online learning[8]. Therefore, educational technology has the potential to enhance students' learning engagement with careful design and sound pedagogy[9]. Among the research into learning engagement and online learning, most of them used a quantitative methodology that utilized surveys or questionnaires, particularly self-reported Likert scales as the measurement. Only a few research has used the objective data obtained from DLMs to explore student engagement and their learning performance. In studies that have utilized students' online learning log data, frequency measures such as the number of viewing contents are the most typical measures used to explain the individual difference in online learning. However, some studies have claimed that frequency counts of activities are minimally relevant to engaged learning and that such measures are limited to suggesting instructional interventions [10]. In this context, it is critical to identify the appropriate indicators of learner differences and better predictors of learning performance so that instructors may take effective interventions during the teaching process.

2.2 Learning engagement and learning performance

Measuring students' learning outcomes and forecasting their learning performance brings about various benefits, including introducing appropriate interventions to the learning process and assessing the quality of courses. Student online learning and term assessment grades are the most evident predictors of learning performance and success [11]. In this study, we define students' learning performance as their final test scores of the Intermediate Interpreting and Translating Course.

Student engagement can predict final exam success [12] [13]. Lee and Davis (2018) [14] found that for the content/learning-related learning outcomes, behavioral engagement had the strongest influence followed by affective engagement while cognitive engagement was not a significant predictor.

Among the research on learning engagement and performance, only few resorted to LMS to examine the relationship between these two important elements in teaching process. Some researchers found that participation indicators and patterns are strongly correlated with learning engagement [15] and academic performance [16]. Because LMSs provide analytic functions or summarized reports to instructors, tracing usage data from LMSs is a feasible method of capturing students' learning behavior. Utilizing LMS data helps instructors identify how students perform on the course, which is of great significance and assistance for the instructors to redesign some of the online teaching activities according to students' responses and provide at-risk students with individual support [17]. Hence, resorting to the LMS to collect,

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measure, and analyze data about learners for purpose of optimizing online teaching and learning procedures and activities is conducive to enhancing online learning performance. Whereas few attempts have been made to identify effective measures of online learning engagement and explore their effects on learning performance. Soffer and Cohen (2019) [17] observed that student engagement in online learning had a positive effect on their final performance. Wang (2017) [18] explored the relationship between behavioral engagement and achievement in foreign language settings and found that behavioral engagement in online activities has a significant effect on achievement.

In addition to the frequency measures in online learning, some studies have focused on the quality rather than the quantity of online participation. Asarta and Schmidt (2013) [16] examined the access patterns in terms of 36 online lesson materials and concluded that the overall frequency of access exhibited the weakest correlation with course performance while pacing, anti-cramming, and consistency were significant predictors of course achievement. Nevertheless, more research is needed on the relationships between each dimension of online behavioral engagement according to the LMS data and learning outcomes to identify the crucial factors of students' behavioral learning engagement that will affect learning performance.

2.3 Gender differences in online learning engagement and learning outcome

Gender has long been investigated in educational research. There are studies indicating that gender differences exist in learning engagement and learning outcomes. Some researchers found undergraduate female students were more engaged than male students [19] [20]. Among all the engagement, behavioral engagement was found to be significantly associated with gender [21]. Han and Shin (2016) [22] observed there were potential connections between mobile LMS use and students' gender. Wu et al. (2020) [23] examined gender differences in academic achievement and found that female students had significantly higher outcomes than male students. In contrast, other researchers found neither significant gender differences in students' learning engagement [24] nor significant gender differences in students' learning performance [25].

The previous research either showed contradictory results about gender differences in student engagement and performance or did not sufficiently examine whether the gender of students affects their online learning activities. Accordingly, exploring the gender differences in learning engagement reflected by the LMS data and learning outcome may add to EFL teaching and learning literature and have both methodological and practical significance. Therefore, this study aims to compare male and female behavioral learning engagement as well as learning performance during the period of pandemic-induced online learning to determine whether one gender engaged more and performed better than the other.

3. Present Study

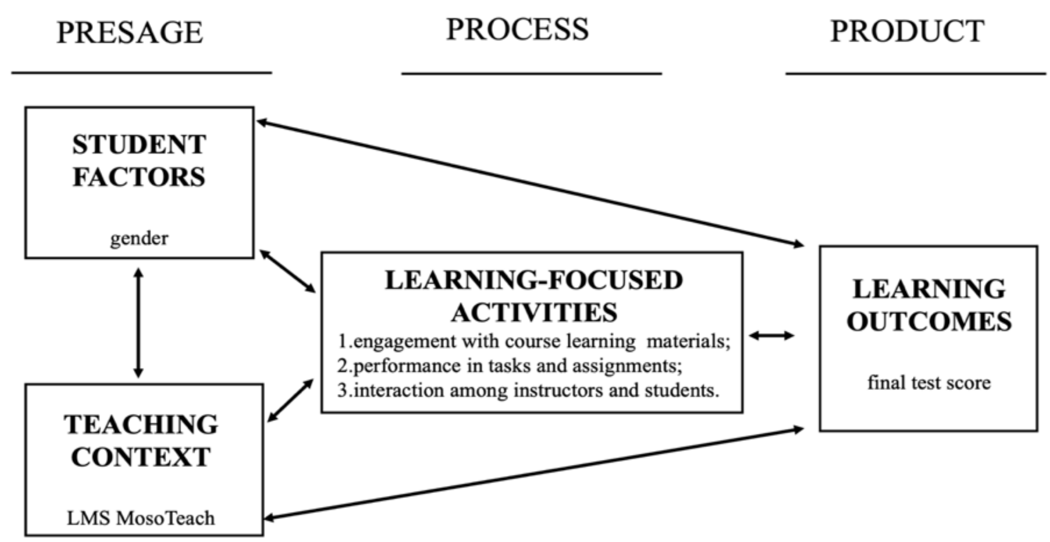

Figure 1: The refined '3P' model of online teaching and learning

John Biggs's 3P (Presage-Process-Product) model demonstrates that student factors, teaching context, on-task approaches to learning, and the learning outcome mutually interact forming a dynamic system [26]. Presage factors refer to what exists prior to engagement that affects learning. On the student side, this includes factors such as ability and gender; on the side of teaching context, it includes the nature of the content being taught, methods of teaching and assessment, and so forth. These factors interact to determine the ongoing approach to the learning task, which in turn determines the learning outcome. This article aims to fill the gap that no research has explored the relationship between online behavioral learning engagement and performance in an EFL fully online course based on the refined Biggs's model in Figure 1. It examined characteristics of students' online behavioral learning engagement in EFL and their impact on learning outcomes and at the same time explored whether gender differences exist in online learning engagement and learning performance. Students' behavioral engagement was explored by analyzing the data generated by the LMS MosoTeach complemented by the analysis of a survey. Students' learning performance in this study is embodied by their final test scores.

When exploring students' engagement in online learning, students' activities are usually classified into three categories: engagement with course learning materials, performance in tasks and assignments, and interaction among instructors and students [17]. In this study, we describe activities in all these three categories and identify significant LMS data indicators to predict course achievement.

The following questions guide this research:

What are the status and characteristics of Chinese undergraduates' learning engagement in a fully online course of EFL?

Can students' online learning engagement represented by data on MosoTeach predict their learning performance?

Is there any gender difference in students' online learning engagement and learning outcome?

3.1 Participants

The research population includes 153 second-year undergraduates in a comprehensive university in eastern China. Among these students, 44 students who have passed College English Test Band 6 (CET-6) or have not passed College English Test Band 4 (CET-4), a national examination testing the English proficiency of university students, were removed to control the English proficiency level of the sample. At the beginning of this study, all the 109 students gave their consent to voluntarily participate in this study which lasted 16 weeks. The students were also informed that the performance score generated by the LMS MT would account for 30% of their total course score and the final test score account for 50% of the total course score. The rest 20% of the course score consisted of the score of their online midterm examination. The average age of the participants (32 male students and 77 female students) is 19.9. Their major includes both liberal arts, science and engineering. They have 3 periods of English class, which include 135 minutes each week. The course, Intermediate Interpreting and Translating, was taught by the same instructor with the same material on the LMS MT.

3.2 Data collection and measures

The study collected data from the above 109 non-English major students who had taken the Intermediate Interpreting and Translating fully online course during the spring semester in 2022. All the data were on the LMS MT, which is one of the most popular intelligent LMSs in China. MT has both the mobile phone application and webpage. It supports mobile learning through an app (see Figure 2 for its mobile interface). MT is specially designed for intelligent teaching in a mobile environment which facilitates teachers to send notifications, share both video and non-video learning resources, arrange individual or group tasks and assignments, correct students' assignments, organize discussions, deliver votes or questionnaires, conduct brainstorming or discussion activities, hold quizzes, and other forms of teaching activities. MT can also effectively track students' learning activities, and record students' learning experiences. It automatically records the number of students' sign-ins, the time span of watching video resources, times of watching non-video learning resources, times students participate in classroom activities, brainstorming, discussion, etc., and calculates the average score of online quizzes. MT also generates the final performance scores of students and learning situation analysis on each student. The in-class activities in this research mainly refer to students answering the instructor's questions and interpreting short videos by turning on their camera and microphone in the video conference. Brainstorming requires students to give their own answers to translating exercises. MT enables students to learn the course materials provided by the instructor anytime and anywhere by using their fragmented

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time. Before class, the instructor uploads all kinds of learning materials including video resources and non-video resources to MT and gives a pre-class previewing assignment, which requires students to make full preparation for the class. During the online class, the instructor interacts with students by holding brainstorming, in-class activities such as video interpreting, group translating tasks, quizzes, etc., and gives students feedback as soon as the activities are completed. After class, the instructor assigns individual or group tasks to students on MT and asks students to give peer evaluations on their fellow students' assignments, and then the instructor grades the assignment with detailed comments to each student or group. In all the activities, video-watching and accessing non-video resources belong to activities of course learning materials. Brainstorming, attendance, and quizzes can be categorized into performance in tasks and assignments. In-class activities and discussions belong to interactions among instructors and students. At the end of the term, the instructor downloads the learning status analysis automatically generated by MT. In this study, we have chosen 7 raw log variables that seemed most useful to represent the students' behavioral learning engagement in the online Intermediate Interpreting and Translating course. The 7 variables included the length of time that students watched the video resources, and the times they accessed the non-video additional resources or participated in the in-class activities, brainstorming, and discussions. The analysis data also included average scores of students' online quizzes and their attendance scores. If the students sign in before class, they will get two points. If they are late for class or leave class ahead of time, they will get one point. If they do not sign in, they will get zero points. The online quizzes consist of objective questions concerning translation skills exercises. When students finish the quiz, they can see their marks automatically given by MT immediately.

At the end of the term, the online final test scores (which ranged from 0 to 100) were used for measuring students' learning performance. The final test is constituted by both objective multiple choices and subjective translation questions.

This study collected both quantitative and qualitative data. We use students' learning activity data generated by MT, the online final test scores of the course, and students' answers to an online survey to make analyses. The survey was given at the end of the semester through Wenjuanxing, a popular online survey tool (http://www.wjx.cn/) in China. The first part of the questionnaire collected students' background information such as student number, age, gender, major, and whether they have passed CET-4 and CET-6 or not. The second part includes two open-end questions such as what kind of online teaching activities benefit them most and what are their major problems and difficulties during online learning of the course. A full version of the questionnaire is included in the Appendix in both Chinese and English. After the online final examination, we analyzed 109 students' final exam scores and the three categories of learning data generated by MT, including minutes of watching video resources, times of accessing non-video resources, times of participating in brainstorming, attendance score, average online quiz score, times of taking part in in-class activities and discussion.

3.3 Data analysis

We used a combination of quantitative and qualitative methods to investigate the research questions. A descriptive statistics of SPSS 26 was used to analyze the situation and characteristics of student online behavioral engagement, a multiple linear regression was conducted to predict students' final test score, and an independent sample test, as well as a partial correlation analysis, were utilized to analyze gender differences and the effect of gender on the relationship between engagement and performance. We also analyzed students' answers to the online survey questionnaire in order to better understand the data on MT.

4. Results and discussion

4.1 Students' online learning engagement status and performance

According to the descriptive statistics analysis in Table 1, many students had access to online video or non-video resources. They had a high attendance rate in this online course. They also participated in most of the brainstorming and discussion activities. As for in-class activities, only a few students took part in this interaction. In terms of quiz scores, it indicates that the majority of students have achieved the teaching goal that the instructor set (mean = 83.339).

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Table 1: Raw data of behavioral engagement on MT and final test score

N =109	Online activities	*Minimum*	*Maximum*	*Mean*	*SD*
CLM	Video Watching (minutes)	6.13	250.75	232.406	40.308
	Accessing resources (times)	41	66	64.73	3.222
PTA	Attendance (points)	84.78	100	98.714	2.823
	Brainstorming (times)	0	16	15.03	2.217
	Quizzes (points)	35	96.67	83.339	11.279
IIS	Discussion (times)	9	19	15	3.308
	In-class activities (times)	0	7	1.2	1.784
Engagement	Performance score (points)	55	99	87.49	7.453
Performance	Final test score (points)	55	92	78.367	7.353

Note: CLM=Course learning materials; PTA=Performance in tasks and assignments; IIS=Interactions among instructors and students; SD = standard deviation

According to the scores (from 0 to 100) of every activity generated by MT in Table 2, among the three categories of online activities, interaction among instructors and students has the lowest scores.

Table 2: Behavioral engagement scores (from 0 to 100) generated on MT

N =109	Online activities	*Minimum*	*Maximum*	*Mean*	*SD*
CLM	Video Watching (minutes)	0	100	95.55	15.690
	Accessing resources (times)	70	100	98.88	3.594
PTA	Attendance (points)	84.78	100	98.714	2.823
	Brainstorming (times)	0	100	76.57	19.937
	Quizzes (points)	35	96.67	83.339	11.279
IIS	Discussion (times)	46	100	74.47	13.984
	In-class activities (times)	0	100	20.61	30.170

Students' answers to the open-end questions in the online survey revealed that they find some teaching activities are rather beneficial to them, such as the live streaming sessions on interpreting and translating skills and interactions between students and the instructor. These activities belong to two categories among the total three classifications, which are course learning materials and interactions between students and the instructor. The fact that students feel the live streaming sessions on interpreting and translating skills are very helpful may be due to using online teaching materials is convenient, less stressful, and more effective for students [25]. According to the result, EFL instructors should make an effort to provide students with as many helpful multimodal learning materials as possible which enable students to learn at their own pace. As for the implementation of interactive online activities, for one thing, institutions should guarantee the quality of Internet streaming, and for the other, instructors should create a harmonious and friendly learning community on the LMS and design more flexible and diverse interactive activities as well as provide real-time feedback to students' performance.

As for the challenges during the online learning process, students' responses include "sometimes the network is not well-connected", "can't concentrate in the online class because there is no face-to-face communication with the instructor", and "feel quite nervous because sometimes can't follow the online activities" and so on. The network problem can partly explain the low participation rate of the in-class activities because in-class activities require students to connect with the instructor with both their camera and microphone turned on. According to the class observation, some students volunteered to answer questions but failed to successfully connect with the instructor, so they had to give up the opportunities. That some students can not follow the online activities can explain the relatively low participation rate of discussion to some extent. As the absence of face-to-face communication might lead to a sense of isolation and a lack of community, the online activities of a course should be carefully designed to promote interactions among instructors and students. Meanwhile, instructors should recognize that online communication takes longer than classroom communication in most cases and therefore more time should be allowed in the course plan for online activities requiring interaction among students than might be provided in the course plan for traditional offline classes [27]. According to students' answers to the survey in this study, poor quality of internet services is the main factor that impacts students' behavioral learning engagement in an online course. As internet access is essential for the success of online teaching and learning, institutions should try every means to improve the campus internet infrastructure to prepare for possible force majeure such as the COVID-19 pandemic when most students are on campus and large-scale online learning is necessary. The other important challenge against online learning is the distraction of other social media. EFL instructors should make great efforts to design more interesting

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interactions to help students focus on the content of online courses.

4.2 Predicting students' learning performance based on their online engagement

Spearman correlation analysis was conducted between seven activities on MT and the final test score because not all independent variables are normally distributed. From Table 3 we can see that there are significant positive relationships between five online learning activities and students' final test scores, with the following coefficients respectively, $r_{quizzes}$ = .407, $r_{in\text{-}class\ activities}$ = .307, $r_{brainstorming}$= .270, $r_{attendance}$ = .217, $r_{accessing\ resources}$ = .216.

Table 3: Spearman correlations between online learning activity and final test score

N=109	Course learning materials		Performance in tasks and assignments			Interactions among instructors and students	
Activities	VW	AR	BRS	ATD	Quiz	I A	Discussion
Final test	.128	.216*	.270**	.217*	.407**	.307**	.144

Note: VW=viewing video, AR=accessing resources, BRS=brainstorming, ATD=attendance, IA=in-class activities; *p<.05, **p<.01; r=0.1 (small effect size), r=0.3 (medium effect size), r=0.5 (large effect size).

Multiple linear regression was then conducted to develop a predictive model in which "student final score" was the dependent variable. As in Table 4, this analysis process generated the best predictive model of students' final scores (F = 12.103, p <0.001). The method of "Stepwise" showed that two independent variables significantly predicted students' final test scores, The beta weights, presented in Table 4, suggested that online quizzes (β = .308, p < 0.01) and in-class activities (β = .257, p < 0.01) explained 18.6% of the variance in students' final test scores. According to the results, it follows that students' final learning outcome is determined by interactions involving active participation and the interactions they have with the instructors. Following this result, it seems possible to obtain a measure of behavioral learning engagement by analyzing log file data in LMS that is meaningfully linked to students' final test outcomes. This finding affirms the importance of designing and including more active interaction in the online learning course. Meanwhile, since the LMS MT enables instructors to trace students' learning activities for the evaluation of students' learning behavior through formative and summative assessments, instructors may help those high-risk students enhance their learning motivation and engagement according to data on the LMS.

Table 4: Multiple Linear Regression

	Variables	R	R^2	Adjusted R^2	F	Beta	t	Tolerance	VIF
DV	Final test	.431	.186	.171	12.103***				
IV	Quiz					.308	3.470**	.975	1.025
	In-class activity					.257	2.897**	.975	1.025

Note: DV = dependent variable; IV = independent variable; **p<.01; ***p<.001

Some implications may be drawn from the regression analysis result. Firstly, both these two kinds of activities require students to perform at the higher levels of thinking in Bloom's taxonomy, which are application, analysis, synthesis, and evaluation [28]. The result here indicates that engagement in high-level learning activities makes more contribution to predicting students' learning performance.

Secondly, in this research, both in-class activities and quizzes belong to interactive activities between learners and the instructor. In-class activities require students to answer real-time questions and they may get the instructor's feedback on their answers immediately. Likewise, when students finish the online quiz, the instructor gives feedback on students' performance according to the statistics of MT. The result confirms that interaction and communication between students and faculty had a major influence on students' online learning [29].

Thirdly, as both online quizzes and in-class activities belong to in-class engagement while activities such as video viewing and accessing learning materials can be classified into pre-class engagement, this result added evidence to the finding of Lee et al. (2018) [14] that total learning outcomes were affected significantly by in-class engagement than pre-class or after-class engagement to a greater extent.

Last but not least, the result that online quiz scores have more predictive power than other activities in accounting for students' learning success indicates that "the quality of learning behaviors rather than simply the frequency of access" [2] should be taken into consideration. Therefore, the key to engaging students is not only to require participation in the online activities but also to design activities with a value that can improve the quality of the course. Creating activities that engage students in critical thinking not only helps create a community of learning but also facilitates students' in-class engagement and therefore is critical to the acquisition of knowledge.

Compared with quizzes and in-class activities, video watching and accessing resources belong to passive interactions, so they were not found to be significant predictors of success on the final exam. The reason why variables such as video viewing and accessing resources in this research did not predict the final test score may be associated with the phenomenon of "fake engagement", which is defined by Mercer et al. (2021) [30] as "the behavioral actions that are deliberately enacted by the learners in order to create the impression of engagement in instances when in fact, learners are thinking about or doing something completely different to the task at hand". It is possible that some students only watched videos or accessed the non-video resources for the purpose of gaining bonus points on MT but did not really focus on the content of the learning resources. Authentic engagement requires students to be cognitively and emotionally invested in the class activities. Therefore, it is critical for instructors to find the appropriate approach to distinguish authentic engagement from fake one when analyzing the data on LMSs.

In this research, most of the students participated in the brainstorming activities and could get points for participating in the task so the difference in brainstorming scores was not so obvious. This may be the reason that brainstorming did not make a contribution to predicting the final test score.

The prediction of success in final test scores emphasized the importance of participation in quality activities on the LMS. Although LMS log data provides a variety of variables, not all activities have an equal function in predicting students' learning performance. Activities such as online quizzes and student-instructor interactions in this research have the most significant predictive power on learning performance. These two-way communicative activities between students and instructors allow instructors to give immediate feedback to their students' real-time output and promote participation and engagement of students, which ultimately improve students' performance [31]. Educational practitioners and instructors need to redesign their courses by including new elements and activities or improve the existent activities according to the findings in this study in order to enhance the online teaching quality.

4.3 Gender differences in learning engagement and performance

Table 5: Comparison of gender on all the variables

	Variables	Male (n=32)		Female (n=77)		*MD*	*t*	Effect size (Hedges' *g*)
		Mean	SD	Mean	SD			
CLM	Video Watching	211.715	58.173	241.005	12.565	-29.291	-2.412***	0.767
	Resources	63.34	5.159	65.31	1.656	-1.968	-2.113*	0.634
PTA	Brainstorming	13.81	3.623	15.53	.867	-1.720	-2.654*	0.826
	Attendance	97.407	4.259	99.257	1.705	-1.850	-2.379*	0.684
	Quizzes	78.109	14.127	85.513	9.113	-7.404	-2.737**	0.685
IIS	In-class activities	1.03	2.055	1.27	1.667	-.241	-.642	0.134
	Discussion	13.09	2.595	15.79	3.262	-2.698	-4.570***	0.876
Engagement	Performance Score	82.50	10.552	89.56	4.324	-7.058	-3.658**	1.046
Performance	Final Test	76.031	6.673	79.338	7.444	-3.306	-2.175*	0.457

Note: CLM=Course learning materials; PTA=Performance in tasks and assignments; IIS=Interactions among instructors and students; *SD*=standard deviation; *MD*=mean difference.
**p*<.05, ***p*<.01, ****p*<.001; *g*=0.2 (small effect size), *g*=0.5 (medium effect size), *g*=0.8 (large effect size)

T-tests were used to determine whether there were gender differences in students' online learning engagement as well as English final test scores. Students' behavioral learning engagement can be represented by the performance score generated by MT. It is evidently shown in Table 5 that female students scored higher than male students for each of the 9 variables. Since the numbers of the samples were different, Hedges' effect size g was used to determine if the mean differences were practically significant. Table 5 shows that there were significant differences in online activities including video-watching, accessing resources, brainstorming, attendance, quizzes, and discussion between different genders. The average video-watching time of female students was significantly longer than that of male students. Times of accessing resources, brainstorming, discussions, and attendance of female students are more than that of their male counterparts. The mean scores of online quizzes and final exam scores of female students are also higher than male students. The effect sizes were from medium to large according to Cohen (from 0.634 to 0.876). Our results showed that no differences exist between male and female students' in-class activities participating times in the LMS MT. The fact that the average

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participating times of in-class activities is 1.2 may explain why the difference is not statistically significant. Only a few students who were very confident with their English proficiency or attach great significance to the bonus score awarded to them for taking part in the in-class activities were frequently involved in this activity. But female students' participating frequency (mean =1.27) is still higher than that of male students (mean =1.03). So, this result may be related to the sample and total times of in-class activities, which should be explored in future research. There were also significant gender differences in performance scores generated by MT which represent students' behavioral learning engagement and significant gender differences in students' final exam scores, which is in line with findings of Krasodomska & Godawska (2020) [25] that female students achieved on average higher scores than male students. This calls attention to the challenges male students might confront in the online learning context, which could intensify males' existing underperformance in terms of overall academic performance. Therefore, male students' potential disadvantages in terms of behavioral learning engagement during mandatory online learning should not be overlooked.

Table 6: Partial correlation coefficients of performance score on MT and final test score (N =109)

Control variables			Performance score	Final test	Gender
-none-[a]	Performance score	Correlation	1.000		
		Significance (2-tailed)	.		
		df	0		
	Final test score	Correlation	.354	1.000	
		Significance (2-tailed)	.000	.	
		df	107	0	
	Gender	Correlation	.433	.206	1.000
		Significance (2-tailed)	.000	.032	.
		df	107	107	0
Gender	Performance score	Correlation	1.000		
		Significance (2-tailed)	.		
		df	0		
	Final test score	Correlation	.300	1.000	
		Significance (2-tailed)	.002	.	
		df	106	0	

Our results challenge the argument of female students' potential disadvantage in the virtual classroom and reveal their higher levels of behavioral engagement and learning performance during the online EFL learning process compared to their male counterparts, which is in line with the study result of Korlat et al. (2021) [3]. The finding is also consistent with the result found in a previous meta-analysis, which reported an effect ($d = 0.36$) of gender on academic performance in distance learning [19] and that female students averagely scored higher than male students [24]. It is important to note that the effect sizes of gender differences in online learning engagement found in our research are from moderate to large and the effect size of gender differences in final test scores are very close to moderate. According to these results, we can say that those female undergraduate students engage more than their male counterparts in the behavioral aspect and perform better in terms of academic performance in online learning environments. This is not surprising given female students' higher levels of engagement in school-related tasks [32] and being more study-oriented [33]. It might be that female students transferred their established learning habits into a new learning context when institutions switched to online learning. Another reason may be attributed to male students' potential disadvantages regarding interaction with instructors and intrinsic value [3]. This result may suggest that female students also have higher cognitive and emotional engagement than male students, which should be confirmed in future research.

Due to the fact that gender may have an effect on student behavioral engagement and learning performance, we conducted partial correlation analyses using data of students' behavioral engagement represented by the performance score generated by MT and their final test scores with the variable of gender being controlled. From Table 6, we can see that there is a significant positive relationship ($r = 0.3$, $p < 0.01$) between students' online behavioral engagement and learning performance when the factor of gender is controlled. The effect size is medium.

Since the final performance score generated by MT may represent students' total online behavioral engagement, we drew scatter diagrams in Figure 2 and Figure 3. Figure 2 shows a statistically significant correlation exists between the final performance scores and final test scores among all the 109 participants. The result confirms the relationship between students' learning engagement and achievement. It would be helpful for instructors in higher educational institutions to use a tool such as an

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intelligent LMS to monitor student engagement over time. This kind of digital LMS would enable teachers to manage the learning process and meanwhile provide students of different levels of engagement with customized support and help [13]. The ranking list on the LMS may also be helpful to stimulate students to regulate their engagement. Therefore, it may be a facilitator to improve students' emotional engagement.

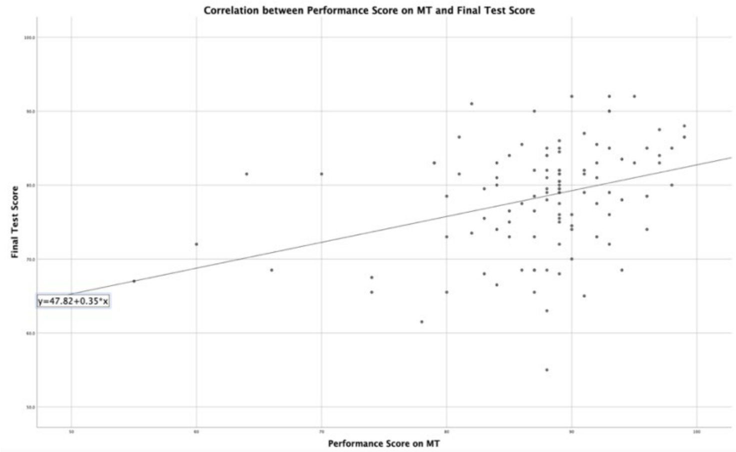

Figure 2: Correlation between performance score on MT and final test score on all participants

Figure 3 shows that the correlation is stronger in female students (r = 0.41) than in male students (r = 0.29). Hence it is important to pay special attention to the gender factor that mediates student online learning engagement and learning performance. EFL instructors should consider individual differences while designing online teaching activities with the aid of the LMS. Educators in higher education institutions should pay attention to the heterogeneity of students, and future studies on why gender has such influence on the relationship between learning engagement and performance as well as how to enhance male students' online learning engagement are necessary.

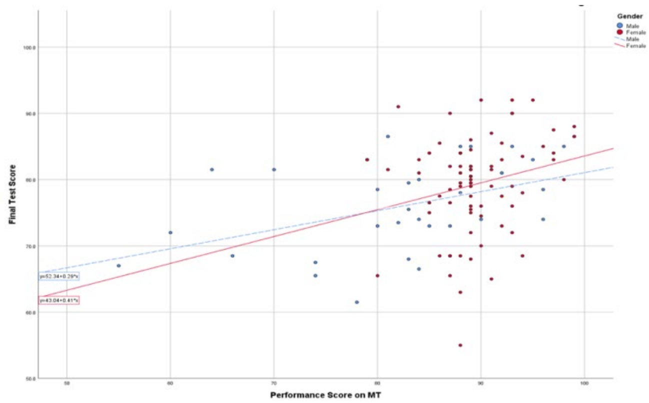

Figure 3: Correlation between performance score on MT and final test score in different gender groups

5. Conclusion

This research investigates the relationship between behavioral learning engagement indicated by LMS data and the learning performance of a fully online EFL course as well as the effect of gender on the relationship.

The first finding in this study is that undergraduate students can devote themselves to the online EFL course with the aid of the LMS during the COVID-19 pandemic period. Most students showed a higher engagement with the course learning materials and attendance rate than in other online activities, such as discussions, quizzes, and interactions with the instructor. According to students' different online learning engagement and learning performance, they can be divided into three clusters. 92.66% of students constitute the largest group, who have high learning engagement as well as high learning performance.

The second main finding is that students' learning outcomes can be predicted by data on the LMS MT, with the online quizzes and in-class interaction contributing most to explaining the success of the final test.

The third important finding is the existence of gender differences in online behavioral learning engagement and learning outcomes, favoring females over males. Female students participated and collaborated more actively in the online class activities. They also performed better than their male counterparts. Gender as a personal factor is not only important to affect students' behavioral engagement and learning performance but also influences the relationship between their engagement and academic performance.

As traditional EFL teaching approaches in higher education institutions are facing an increasing challenge because of the reduction in available teaching time and the spread of epidemic or other force majeure factors, a shift from traditional classroom teaching to online, distance, or electronic teaching with aid of an LMS should be attached greater significance in the future. In this context, understanding the gender difference between students' behavioral engagement in online learning and identifying variables that can predict success on the final examination is conducive to improving teaching and learning quality in online courses.

6. Limitations and directions for future research

Though this research sheds light on the utilization of LMS in formal online EFL courses and studies how undergraduate students learn in an online EFL course and what online learning behaviors predict their learning performance, there still exist some limitations to it. First, the sample and institution involved in this study were small and limited. Although the variable in-class activities in this study did not show significant differences between genders and variables except online quizzes and in-class activities did not enter the regression model, these results could be different if the sample were larger or if activities were more than in this study. Future research should apply a larger sample in different types of higher education institutions. It will also be valuable to explore how students' emotional and cognitive engagement during the online process can be measured and managed to help learners achieve better learning outcomes.

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