Learning Analytics as A Predictive Tool in Assessing Students' Online Learning Navigational Behavior and their Performance

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Abstract: Learning Analytics (LA) captures the digital footprint of students' online learning activity. This study describes students' navigational behavior in an e-learning setting by processing the LA data obtained from Blackboard LMS. This is an attempt to understand the navigational behavior of students and the relationship with learning performance. The study was carried out with 88 learners from a Malaysian private university. The course sites' log data and students' performance were analyzed, and the results were as follows: 4 navigational behaviors played an important role in student's academic performance which are active days, total learning time, number of views, and days delayed in accessing the assessment. Active learning from Tuesdays to Thursdays had a significant positive effect on performance. It was found that the higher activities (total learning time, number of journals viewing) translate to better performance. Days delayed in attempting assessments had a significant but mixed effect on performance, depending on the type of assessment. However, the number of logins is insignificant. The findings of this study provide empirical evidence of the importance of self-discipline in online learning and provide instructors with a predictive measure as a call for early intervention to help online students.

Keywords: Blackboard, Learning management system, Learning analytics, Student engagement, Blackboard analytics, Performance

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Introduction

The Sustainable Goal (SGD4) on quality education aims to ensure inclusivity and lifelong learning which can be achieved through distance education or e-learning. Learners can gain education anytime and anywhere, hence promoting inclusivity such that no one is left behind even in adverse situations. It also creates a society of lifelong learning as learning accessibility is easier allowing self-paced and self-directed students learning.

Although recognized for the flexibility of learning anytime and anywhere without the limitation of space and time, e-learning became the central and only mode possible when COVID-19 hit. During this period, with the sudden shift from the traditional setting to e-learning, academicians were faced with the complexity of teaching students who are not physically present. Contradicting the traditional face-to-face classroom setting, the virtual classroom or self-directed e-learning setting would not allow instructors to observe the non-verbal cues, especially through students' facial expressions as well as in-class work to determine if students can grasp the concept being taught. Instructors are also not able to move around the classroom to check on the solutions on students' worksheets and identify the mistakes for instant feedback. In an online setting, these non-verbal cues take place behind the screen, which leaves instructors to just assume that students are coping with the topics taught. To better understand students learning and engagement in an online setting, Learning Analytics (LA) on students' digital footprints is crucial. The Horizon report (2011) defines learning analytics as, 'the interpretation of a wide range of data produced by and gathered on behalf of students to assess academic progress, predict future performance, and spot potential issues.'. The learner's data is collected from the technologically rich learning management system (LMS) that carries the answer for online instructors to investigate pedagogy and instructional design statistically (Grant, 2012; Li & Tsai, 2017; Lockyer & Dawson, 2011; Macfayden and Dawson, 2010; Zhong, 2017) and provide the learning support at the right time (Lockyer, Heathcote & Dawson, 2013; Zhong, 2017).

The usage of various Learning Management Systems (LMS) increased post-pandemic as it was the heavily utilized mode to teach and communicate with students (Duin & Tham, 2020). The Blackboard LMS is among the popular LMS employed to engage with students for the delivery of subjects, interaction with peers, submit coursework, and even conduct the final exams. The Blackboard LMS has a statistic tracking option and stores data that is rich in information to understand the learners' learning type and predict the learners' progress (Kim et al., 2016; Macfayden & Dawson, 2012). The statistic tracking creates a record of the digital footprint in the LMS containing potentially valuable information on learner's login times, items accessed, and the number of times accessed (eg Cerezo et al.,2016; Chatti et al,2012; Kim et al., 2016; Papamitsiou & Economides, 2014; Seo, Kim, & Ju, 2021; Zhang, 2016; Zhong, 2017).

In the last decade, before the pandemic, some studies attempted to investigate students' engagement with various LMS and the links to the grades. Spivey and Macmillan (2013) examined the relationship between remote learning students' efforts measured by the frequency of access on students' performance and found a positive relationship. Li and Tsai (2017) studied the navigational behavior of 59 students in a computer science program and found that those who invested time viewing the online learning materials gained significantly higher examination scores. The navigational behaviors were clustered into the Consistent Use Group and Less Use Group based on statistical quantifiers. Mwalumbe and Mtebe (2017) used various measures (discussion posts, peer interaction, time spent on LMS, number of downloads, login frequency) to investigate the impact of students learning. It was found that time spent in the LMS, number of downloads, and login frequency were found to have no significant impact on students' learning performance. Edwards et al. (2009) investigated the timely access of assignments by 1101 programming students and their impact on their performance. It was found that students who scored at least a B did not delay in attempting the assignment as compared to those who scored C and below. Fenwick et al (2009) also used the same measure which was the days delayed in accessing assignments found that students who earned better grades were those who started two or more days prior to the date. A mixed effect is found using this measure as Murphy et al. (2009) investigated 21 programming assignments and concluded that those who spent lesser time produced better quality assignments. Notably these studies provided a good contribution on the importance of learning analytics prior to the pandemic.

A study done by Zhang, Ghandour & Shestak (2020) analyzing the activity logs on Moodle LMS showed that higher grades is linked to higher logins. Darko (2021) investigated the average time spent by 69 Engineering students in two separate pathways in a semester and over 3 years on BB. The first pathway was a general survey to obtain informed data on ways students engage in their study and the second pathway is using the number of logs made on the BB. Using the Simple Moving Average (SMA), and Product Moment Correlation, the study provides evidence similar to the constructivism learning theory that the increase in BB engagement, the more construct knowledge is developed. Kadoić and Oreški (2021) used data analytics during COVID for YouTube on Moodle LMS and found that students' success is influenced by total views, the number of views in different time segments, and the number of downloads. Summers, Higson & Moores (2022) used library checkout and attendance to investigate the comparison of pre-peri-pandemic learning engagement. Other studies linking online learning navigation and performance were done using specific course programs, select groups, and specific time frames (Cerezo et al., 2016; Romero & Ventura, 2010). The impact of the usage of data analytics during Covid and post-Covid has not been widely explored quantitatively although emergence is evident (eg. Summers et al.,2023; Bashir et al., 2021; Seo et al, 2021). The purpose of this study is to explore unconscious navigation behavior on Blackboard LMS throughout the entire semester. This includes establishing the possible link between navigational key variables and overall performance and further investigating the impact of navigational behavior on different types of assessment.

Method

Sample data and participants

The data is gathered from 88 undergraduate students from a Malaysian private university with an ethnically diverse population. These students are from the American Degree Transfer Program predominantly taking

STEM subjects. 81.8% of them were Malaysians while the remaining were international students from various countries, eg. Myanmar, Sri Lanka, Vietnam, and Bangladesh.

Table 1. General Statistics on the Student Sample

Demographics		Frequency	Percentage
Gender	Male	57	64.8
	Female	31	35.2
Nationality	Malaysian	72	81.8
	Non-Malaysian	16	18.2
Major	Sciences	56	63.6
	Arts	32	36.4

Measures and Data Collection

All the undergraduate modules are managed through the university *Blackboard LMS*, here the announcements, online live lectures, course materials, and assessments can be accessed. Since before the Covid pandemic, lecture recordings are also made available in the system. Statistic tracking is enabled to allow the system to capture the learner's digital footprint or navigational behavior, for each course site.

The course site for each subject includes components such as course announcements, course outlines, course structure, contents, and coursework. Each component can be accessed from the navigation pane on the course site. The course structure, course outline, and other academic-related information are posted prior to the commencement of the semester. Weekly learning materials such as lecture slides, lecture notes, tutorials, and videos are organized into folders by week. For accessing these weekly posted learning materials, three measures were used: *Days active on Blackboard LMS, Total time spent on the course content, and the total number of logins.*

Journal Submission

The setting up of the Journal on *Blackboard* is done by the instructor. These journals are made visible to all students, and they have the option to delete and update their journals. During the semester, students were given many Mathematics questions to solve for each sub-topic and were required to submit their solutions as a weekly entry in the *Blackboard* journal. Over the 14 weeks, each student had a journal of 14 submissions. Since each submission was visible to all, students were able to compare the full solution of every question against others' work, and where needed provided peer feedback. When students were not able to come to a consensus on which solution was correct, the instructors intervened by providing the necessary feedback. For accessing the peer's journal submission with the intent of learning from peers, one piece of data is collected: *The number of journal submissions viewed.* Enabling students to communicate online on the course site is important for online learning. While Badawy and Hugue (2010) showed that online discussions have a positive impact on student satisfaction, the present study intends to investigate whether the viewing of journals could have a positive impact on students' learning performance, as an indication that students learned from peers.

Assignments and Quizzes

The assessments, except the final exams, are organized under a Coursework folder which is placed in the course site pane. The two assessments that are done on *Blackboard* are the assignments and quizzes. The assignments are posted on *Blackboard* as a pdf file on a specified date. Students access the questions and complete the assignment within a week as per the deadline. The assignment report is handwritten and must be uploaded via the submission links on *Blackboard LMS*. Quizzes, on the other hand, have a duration of 30 minutes, although the quiz is being made available on *Blackboard LMS* for one week. Students can take the quiz anytime within the week. The measures of the navigational behavior for these assessments are the timeliness of accessing the assignment and quizzes or the number of days delayed between the day the assessment was posted and the day the student accessed the posted assessments. For example, "1" means the student accessed the material 1 day after the assessment was posted. So, the two data collected from the assessments are *days delayed in accessing the assignment* and *days delayed in accessing the quiz.* Accessing materials promptly depicts self-discipline which is one important requirement of online self-directed learning. Checking on the days delayed came with the idea that the sooner the assessments were accessed, the better their performance (Zhang, 2016).

Results

The course site content is organized to have YouTube videos, Lecture notes, tutorials, and Journal Links. The highest visited course content are the journals comprising more than half of the total, followed by tutorials, lectures, and YouTube videos in descending order, as shown in Figure 1. Journal being the most visited suggests that it is perceived to be more beneficial compared to the lecture notes. A potential reason could be that the lecture notes do not contain as many worked examples as the journals.

The first navigational measure is the days active on *Blackboard* LMS. The student's time spent on the course site is averaged by the day of the week and the data is displayed in Figure 2. It is found that the average time spent per day by the day of the week is somewhat of a bell-shaped curve with the majority of them spending more time navigating the course site on Thursdays. There is a rising pattern before Thursday and drops on Fridays and Saturdays. Further investigation on the link between performance and students' average time spent on *Blackboard LMS* showed that there is a significant positive correlation between students' average time spent navigating the course site and their overall performance on Wednesday, Thursday, and Friday. Table 1 shows the correlation coefficients.

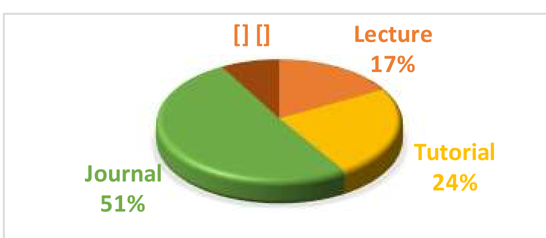

Figure 1: Course Content Accessed by Students

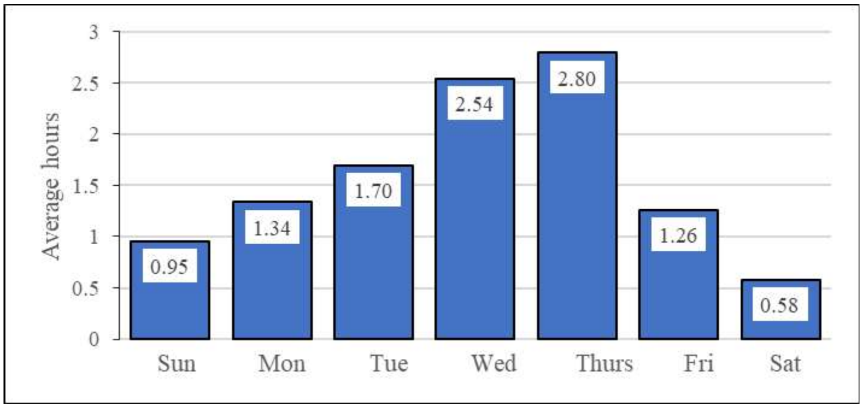

Figure 2: Average Hours Spent Each Day on Learning Management System

Table 1: Correlation between Performance and day of the week

Day of the week	Pearson Correlation
Sunday	0.11
Monday	0.099
Tuesday	0.2*
Wednesday	0.14*
Thursday	0.184*
Friday	0.142
Saturday	0.11

**. Correlation is significant at the 0.05 level (2-tailed).
*. Correlation is significant at the 0.10 level (2-tailed).

The *Blackboard LMS* analytics measures (time spent on course-site, total login clicks, number of journal views, number of YouTube views) were broken into categories low and high using the mean-split and tested using the mean rank test as shown in Table 2. Students who spent a higher time on the course site had a significantly greater effect on their performance ($M=48.57$, $p<0.10$). The total logins did not show a significant difference, hence students who logged on to the course site with a higher frequency did not necessarily have a better learning performance. Journaling made a great impact on student's performance ($M=50.65$, $p<0.05$), indicating that the more frequently students viewed the journals of their peers or their own would increase their learning performance. Similar results were seen for viewing the YouTube videos ($M=72.93$, $p<0.05$).

Table 3 shows the effect of timely access to the assessment on performance. Did the delayed access to the assessment affect the assessment score? Correlation analyses found that there was a significant correlation between the two measures, and the correlation was different for different assessments. For the assignments, students had a good performance on average ($M=79.53$, $SD=3.05$) with low average days delayed in accessing the assignment ($M=0.8$, $SD=1.23$). It was found that there is a negative relationship between days delayed in accessing the assignment and the performance on it ($r==0.564$, $p<0.01$) suggesting that the higher the days delayed in accessing the assignment, the lower the quality of the assignment submitted resulting in poor performance. Surprisingly, the quizzes had opposing results. Student's quiz performance ($M=84.92$. $SD=2.01$)

and days delayed in accessing the quiz (M=1.72, SD=0.99) had a significant positive relationship (r =0.299, p<0.05). This suggests that the longer students took to prepare for the quiz, which is from the interval of the day of the quiz posting and attempting the quiz, the better their performance.

Table 2: Mean rank test for overall performance by the measures from *Blackboard LMS* Analytics

Key Variables	Categories	Mean Ranks	Levene's Test	Significance
Time in Course Content	Low	38.89	0.919	p<0.10
	High	48.57		
Total Login	Low	34. 15	0.105	p>0.10
	Average	43.96		
	High	49.35		
Journal	Low	38.35	0.449	p <0.05
	High	50.65		
YouTube Video	Low	25.63	0.107	p<0.001
	High	72.93		

Table 3: Relationship between navigational behavior on different types of assessment

	Average	Std. Dev	Correlation
Days delayed (Assignment)	0.80	1.23	-.564**
Assignment Performance	79.53	3.05	
Days delayed (Quiz)	1.72	0.99	.299**
Quiz Performance	84.92	2.01	

**. Correlation is significant at the 0.01 level (2-tailed).

Discussion

Does students' access to the course site based on the days active relate to their learning performance?

Students are actively engaging on the course site with inconsistent patterns by the day of the week (Darko, 2021; Yousaf et al., 2018, Zhong L., 2017). This study finds that the students are highly active on the course site between Tuesday and Thursday, and lower on other days. The correlation of these activities with their overall performance is positively significant and is seen during these days. The results of this study recommend that important announcements, postings of material, and deadlines should be scheduled between Tuesdays and Thursdays. The decrease in the activity between Friday to Monday suggests that students used maybe busy with non-academic and personal matters as the weekend approaches.

Does the number of hours spent on the course site relate to their learning performance?

The total learning time or the hours spent on the course site had a significant effect on students' learning performance. There was a significant difference in performance between the students who spent a higher amount of time on the course site and a low amount of time. Past studies have also stated that the longer time spent on the course site leads to a higher overall score (Kim, 2003; Rau and Durand, 2000; You, 2014; Seo et al., 2021). The number of hours spent on the course site is an indication of the time students spent studying a book if it was a traditional classroom setting. This can be used as an important predictive tool to have a constant check on students' accumulated learning time and to identify potential students who might perform poorly in the subjects. Many studies found that the total learning time did not affect academic achievement (Kim, 2011; Han and Jeon, 2015; Mwalumbwe and Mtebe, 2017) but other factors such as the number of access or logins, learning intervals, gender, and age were important.

Does the number of logins on the course site relate to their learning performance?

Similar to most studies (Zhang, 2016; Han and Jeon, 2015; Mwalumbwe and Mtebe, 2017) it was found that the number of logins to the Blackboard LMS Course site did not have a significant association with students' performance. This confers to the notion of "quality versus quantity". More logins do not translate to better performance, instead quality time spent on each login matters. Another possibility that there is no significant relationship is because the files that are posted on the course site such as the PowerPoint slides, notes, and tutorials are downloadable. Some students may have downloaded the files probably in one login per week and accessed them multiple times on their local files. Since the data for the number of downloaded items were not included, the analysis is inconclusive and perhaps useful for future work.

Does the frequency of visiting peers' journals or self-journals and YouTube videos relate to their learning performance?

The inevitable isolation is seen as a drawback in online learning. Discussion boards in Blackboard LMS are usually used as a tool to help with students' communication (Kwon, 2019; Zhang, 2016; Alghamadi, 2019). Deviation from the normal Discussion Board, this present study used Blackboard Journal as a tool for students to interact with peers. The frequency of journal views and YouTube views have a positive significant effect on the student's learning performance. The Journals which were tutorial submissions visible to all students provide the weaker students to learn from the journals of other students.

Does the delay in accessing assignments posted relate to their learning performance?

The delay in assessing the posted assessments would significantly affect the learning performance holds in this present study, however, the effect is mixed depending on the type of assessment. The data shows that students' behaviors varied dramatically for each assessment. An assignment is a component where students are given at most a week to prepare for their submission. Students who started late on the assignments produced output that are not on par with those who have started the assignment early, leading to poorer scores. Starting late here means the Blackboard LMS data shows that students viewed the assignment later than the date posted. The significant negative effect is understandable as not accessing it promptly means that learning activities were not well organized, and students lack self-discipline. Starting late on the assignments forces students to cram up their learning needs as described by Spivey and Macmillan (2013) as “crammed access”. However, it is beyond the data analytics capability to ensure that students viewed the assignment early and started working on the assignments as soon as they viewed them.

The next assessment that was analyzed is the online quizzes, and as opposed to the assignment, showed that the later the quizzes were accessed the better their performance. Quizzes are available for a week but only require 30 minutes to complete once accessed. Students who accessed the quizzes closer to the due date performed better. The understanding of this is that students who took the quiz later had used the prior time to prepare to lead to better performance. Another possible explanation students who delayed taking the quiz might have been familiar with the content knowledge and therefore did not see the need to attempt the quiz as early as it was posted (Zhang, 2016).

Conclusion

Online learning is possibly the future learning model and many higher learning institutions are rapidly developing it. It is a constant effort by the learning institutions to provide quality education and better understand the online navigational behavior that can contribute towards a holistic learning experience. The empirical evidence in this study is the significance of the five navigational behavior on performance which are *active days, total time spent on the LMS course site, frequency of video and journal views,* and *timely access to assignments and quizzes.* This could only be possible with learning analytics and the statistics tracking data stored in *Blackboard LMS*. The data collected show the trail of students’ navigational behavior. In this study, learning analytics has provided evidence that students are active on certain days of the week suggesting that postings of notes, announcements, and other information should be made available between Tuesdays and Thursdays. Higher engagement on these days has shown to have better performance. Delay in accessing the assessments is like attending exams later than the expected time. This is uncommon in a physical class because such behavior is observable and subtle peer or instructor pressure is felt. Unfortunately, the online learning environment fails to create this positive pressure and consequently negatively affects students learning performance. Alternatively, in an online setting, the timeliness is picked up on the analytics stored in *Blackboard LMS*. Delay in assessing assessments may not necessarily work as a disadvantage as this study show evidence that it is based on the type of assessment the delay occurred. In conclusion, the evidence from this study implies that when students engage more time on the *Blackboard LMS*, they are absorbing knowledge and creating new information by processing existing stored information to a better chance of obtaining higher grades. The total number of logins to the LMS course site played no role in determining the performance, suggesting that the number of times students log in is not as important as the time spent on the course site for each login. Students may have logged in maybe just to read an announcement, or multiple times to check their online grade book which does not count for learning time that contributes to higher performance.

We conclude that students' performance improves when they are more active on the *Blackboard* LMS course site. Students should watch the short videos provided, view the journals more frequently, and access assessments in a timely fashion. Noting these good online navigational behaviors, instructors can use the *Blackboard* LA to better understand students' academic standing during the semester and possibly identify students who may fall behind. Early intervention can prevent students of potential risk to fall further behind or failing the subject. Besides that, it is worth investing in a good LMS that is functional and user-friendly to incite students' interest to navigate an LMS. In this age of modernization, everything is done using a mobile. Thus, having a mobile-friendly LMS will make learning convenient anywhere and anytime.

Recommendations

It should be noted that the navigational behavior investigated in this study is infinitesimally small compared to the huge aspects of online learning. Online learning is a complex process involving many other factors, many other technologies, and many other tools. Future research also warrants the need to consider other factors such as prior knowledge, learners' intelligence, motivation level, and learners' cognitive level. In addition, students learning data outside the LMS could also shed some light on predicting learning behaviors. Only through continuous research can online education and students' learning outcomes be improved.

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