CHAPTER 2

IDENTIFICATION OF EXCESSIVE SCREEN TIME IN LEARNING MANAGEMENT SYSTEM DURING COVID-19 PANDEMIC

Aziman Abdullah

ABSTRACT

The shift to fully online learning in higher education due to COVID-19 pandemic has caused the increase of screen-based activities, including learning engagement in the learning management system (LMS). As a result, they may experience excessive screen time (EST). While many studies on screen time adopt a self-report or survey approach, there is lack of attention by scholars in identifying EST based on actual online learning engagement in higher education. Therefore, this study adopted educational data mining (EDM) with box-plot visualisation to identify outliers as indicators of excessive user screen time. The findings show that there are more than 10% of students and instructors who are classified as EST users. To conclude, this study has shed light for higher education on the call for a new policy, quality standard and guideline on how healthy online learning engagement should be effectively monitored to mitigate associated risks with EST towards sustainable development goals.

Keywords Screen time, online engagement, quality education

INTRODUCTION

The COVID-19 pandemic has forced all institutions globally to cope with a new normal by adopting a full online learning through LMS to practise social distancing. For most students who stay

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remotely or at home during a pandemic, the poor quality of Internet service and infrastructure could increase the duration of screen time for student and instructor to engage in online learning. While there is a clear guideline (WHO, 2019) on the limit of screen time for children published by World Health Organisation (WHO), the limit for adults is still unclear. Many studies (Majumdar et al., 2020; Okika & Bukola Blessing, 2017; Pans et al., 2019; Randjelovic et al., 2021) on screen time in higher education adopted self-reporting approaches such as surveys. Not only the survey-based approach limits the accuracy of the actual screen time of the LMS users, the approach also induces information latency, where critical information is received too late for decision to be made, especially when the information is critical and associated with the risk on health. While many scholars have approached ExEDM in the learning analytics domain, there is lack of attention on screen time modelling with EDM in literature.

Therefore, this paper aims to explore the potential measurement model to quantify the frequency of screen time based on LMS log data in higher education. Based on this research aim, research questions for this study are:

RQ1: Is it possible to model EST with an EDM approach?
RQ2: What is the potential impact of EST on higher education?

LITERATURE REVIEW

Screen time is a concept that refers to the amount of time spent using a device with a screen, such as a smartphone, computer, television or video game console (Merriam-Webster, 2021). In literature, this concept has been associated mostly with children due to the level of vulnerability on their growth, either physically, mentally or emotionally (Schmidt et al., 2012). For adults, a study has proven that high level of screen time exposure is linked with migraine in young adults (Montagni et al., 2016). Recent study revealed the correlation between extensive or excessive screen time with the level of problematic smartphone use in the context of students in higher education (Randjelovic et al., 2021). It means, the risk of excessive screen time can occur in university environment, either the activity is for educational purpose like instructional video (Wang & Antonenko, 2017), leisure purpose such as online gaming (Oceja & González-Fernández, 2020), or earning or part time jobs like freelance digital jobs (Bridgestock, 2021).

With the current pandemic situation, using online solutions, especially for emergency remote teaching (Adedoyin & Soykan, 2020) through Internet, has become the primary option for higher education institution to deliver the course teaching in addition of existing e-learning strategies (Aboagye et al., 2020; Alqahtani & Rajkhan, 2020). As a result, screen time becomes more extensive. Users who use their digital device with screen-based activities at night exposed them with a blue enriched light from their device. This exposure can delay the release of sleep-inducing melatonin, a natural hormone in mammals that induce the sleep process (Cajochen et al., 2003; Zisapel, 2018). In other words, when exposed, users will feel awake, and keep using the digital device or consuming digital media, which may disturb their normal sleep time as what is needed for their biological clock (Copertaro & Bracci, 2019; Mazzoccoli et al., 2019; Paganelli et al., 2018).

According to literatures, disturbed sleep time or poor sleep quality not only directly affect personal well-being, social competence and academic performance (Studer et al., 2019) but having risk for critical diseases like cancer (Song et al., 2020), cardio cardiovascular (Hoopes et al., 2020) and diabetes (Knutson et al., 2006; Reutrakul & Van Cauter, 2014). Kadir, Mehmet and Abdullah in their study (Demirci et al., 2015) highlighted the positive correlations between smartphone addiction with depression levels, anxiety levels and sleep quality. In the extreme situation, excessive screen time activity or media use potentially can be related with suicide risk among youth, especially girls (Coyne et al., 2021).

METHODOLOGY

This study adopted the EDM approach to harvest the log data from the LMS Moodle database from one of the public universities in Malaysia. The overall methodology for this study is illustrated in Figure 1.

The LMS log keeps the timestamp and user ID. The software tool used in managing this dataset and creating interactive visualisation is Microsoft Power BI. Figure. 2 shows how the data from two tables in Moodle LMS are configured in the tool.

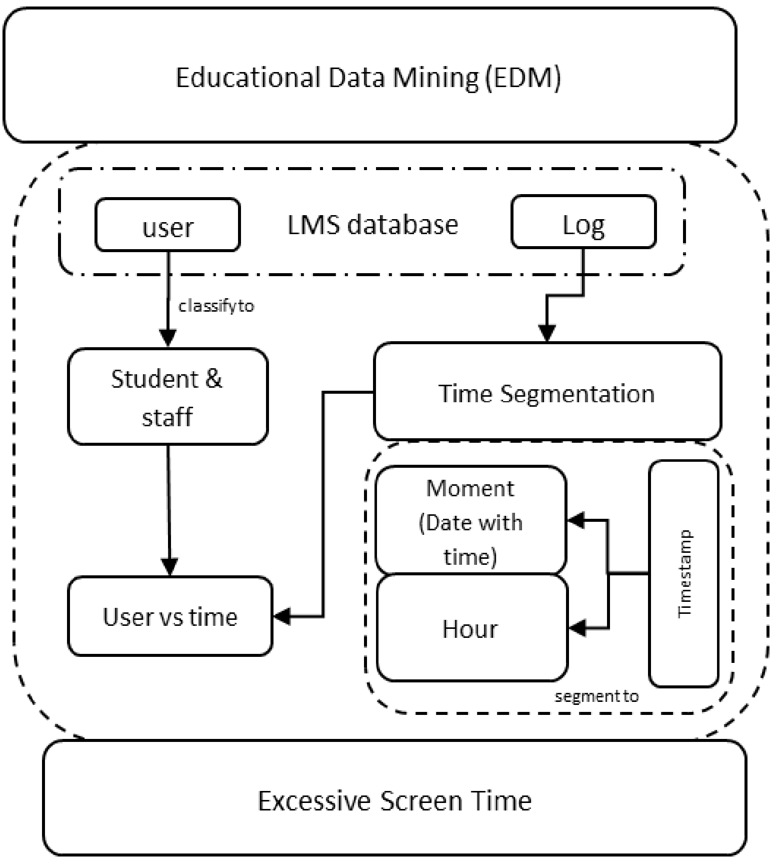

Figure 1: Research Methodology

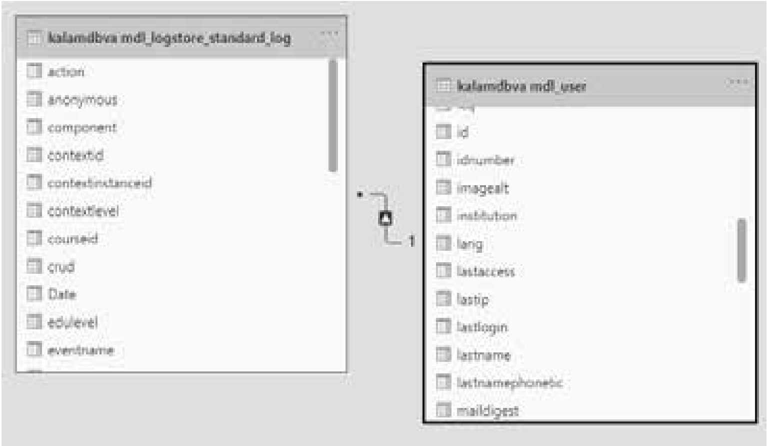

Figure 2: Table Relationship Configuration

Based on user ID, the researcher is able to classify them as students or staff based on their email address pattern. However, their email address have not been disclosed in the analysis in the study. The timestamp data allow researchers to indicate the moment of engagement occurred for every user at every interaction. This data were then processed to extract the date and time of the engagement occurred, as screen time metric shown in Table 1. It means that each user is quantified based on every minute they engaged in LMS.

Table 1: EST Metrics

Metric	Data transformation
Date	#datetimezone(1970, 1, 1, 0, 0, 0, 0, 0) + #duration(0, 0, 0, [timestamp])
Day of week	Date.DayOfWeek([Date])
Week of year	Date.WeekOfYear([Date])
Hour	Time.Hour([Date])

Based on these metrics, the data are analysed by using frequency of engagement for the whole duration of the dataset, which is from 1st February 2020 to 28th October 2020. The anomaly or outliers from the analysis are then considered EST.

The box-plot visualisation is a technique that has been used to identify excessive indicators represented as outliers or anomalies from the dataset.

RESULTS AND DISCUSSION

The context of the dataset used in this study is presented in Table 2.

Table 2: Context of dataset

Context	Value
Institution	Public university
LMS type	Moodle
Number of instructor' account	802
Number of student's account	14, 006
Affected tables & total records	mdl_user : 2, 340 mdl_logstore_standard_log : 11, 598, 542
Size of data	1.18 GB
Data filter	"user_loggin" and "course_view" from mdl_logstore_standard_log
Time range of data	1st Feb 2020 – 28th Oct 2020

Before determining how many users that potentially experience excessive screen time, this study analyses the total screen time on a daily basis for the period of the dataset shown in Figure 3. The metric used for this analysis is the total online learning engagement from the dataset. The metric does not represent the total number of users, instead the total number of transaction or screen time occurred in LMS.

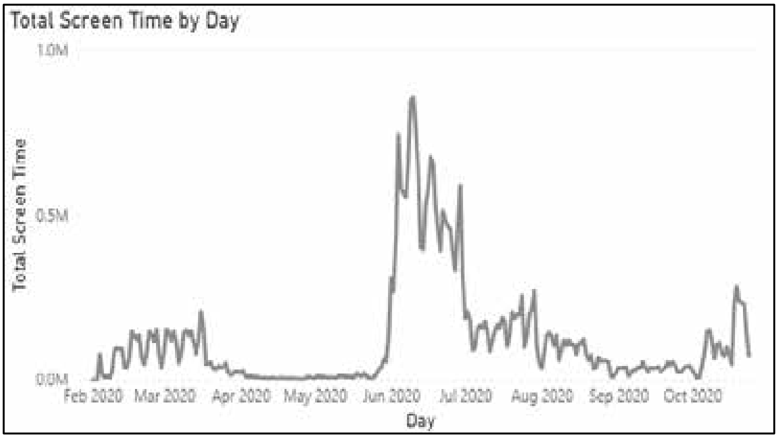

Figure 3: Screen Time Daily Pattern

Figure 3 shows the spiking pattern in June 2020, indicating the increase of screen time in a day. This could be a sign of excessive screen time. However, this study further validates the assumption by segmenting the analysis based on the hour the user screened to access LMS. Figure 4 shows the number of users, including students and instructors who have at least once screened during different time.

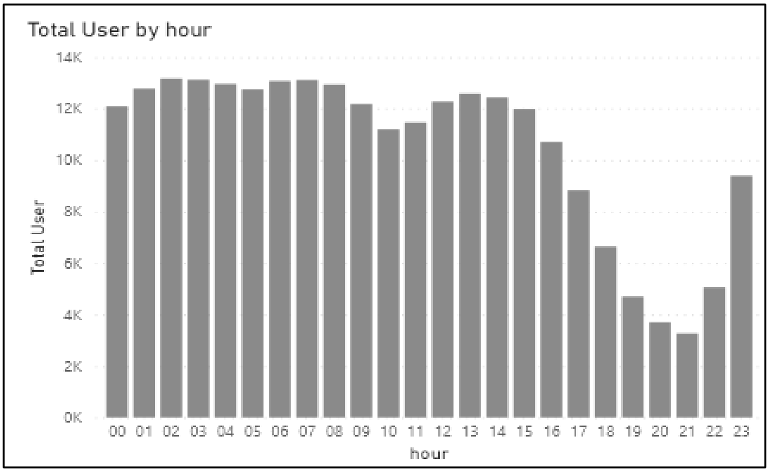

Figure 4: User Screen Time Frequency

Hour	Sunday	Monday	Tuesday	Wednesd	Thursday	Friday	Saturday	Total
0	3053	6763	6626	6727	6868	5902	2456	38395
1	3416	7770	7755	7426	7895	7120	3245	44627
2	4121	8800	8688	8305	8957	7552	3951	50374
3	5173	9007	8655	8351	8793	7774	4525	52278
4	6166	8549	8543	8062	8439	7058	4863	51680
5	5972	8165	8321	7875	7928	6094	5018	49373
6	6475	9039	9036	8592	8819	7631	5495	55087
7	6503	8735	8899	8521	8419	7874	5470	54421
8	5978	8216	8305	8124	8141	7294	4934	50992
9	5280	6805	6703	6805	6996	6281	4305	43175
10	4719	5330	5320	5333	5358	5002	3553	34615
11	5314	5611	6224	6239	5927	5366	3883	38564
12	7080	7615	7701	7901	7636	6547	5482	49962
13	8008	8445	8457	8585	8369	7252	6329	55445
14	8013	8169	8329	8573	8031	6806	6214	54135
15	7117	7378	7175	7414	7105	5575	5624	47388
16	5334	5338	5266	5618	5346	3946	4102	34950
17	3539	3423	3471	3676	3609	2634	2813	23165
18	2120	2121	2178	2177	2348	1766	1792	14502
19	1302	1258	1327	1393	1453	1042	1064	8839
20	845	827	910	1173	939	729	717	6140
21	762	759	766	851	803	584	636	5161
22	1552	1309	1372	1437	1305	850	814	8639
23	4035	3637	3676	3719	3259	1494	1600	21420
Total	111877	143069	143703	142877	142743	120173	88885	893327

Figure 5: User Screen Time Matrix

What can be highlighted from the results in Figure 4 is there are many users who access LMS after midnight or during typical sleep time. This could be a potential indicator of users that experience excessive screen time. To better clarify the assumption, this study further analyses the day of week versus hour presented in Figure 5 as user screen time matrix. The colour from yellow to red indicates the value intensity, representing the total number of users who screened based on the contextual day and hour. The yellow box highlighted in the figure indicates that there are many users who were screening during the typical sleep time or after midnight.

This results however did not segment the type of user, either they are student or instructor in a form of continuous pattern. To better indicate number of students and instructors who potentially experience excessive screen time, this study analyses the data in time series by filtering the time between midnight to 3 AM and categorised to the type of users. Figure 6 and Figure 7 show the analysis of student and instructor screen time during the filtered hours in a day over for the period of the dataset.

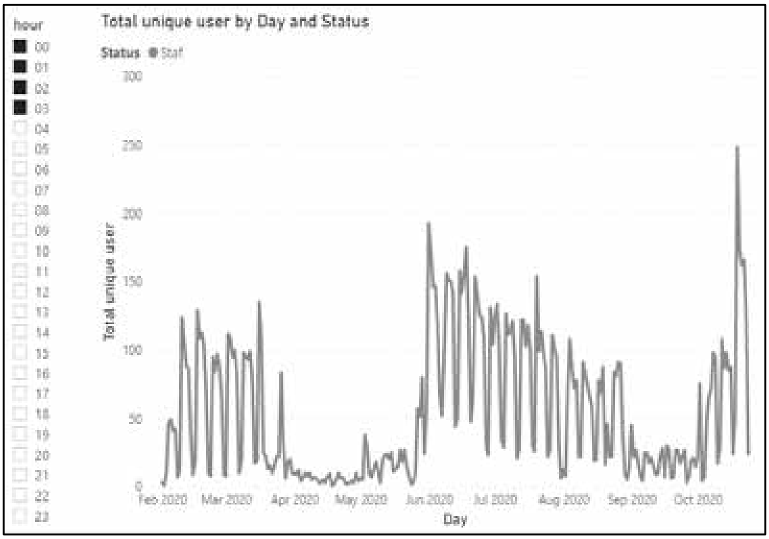

Figure 6: Instructor EST Pattern

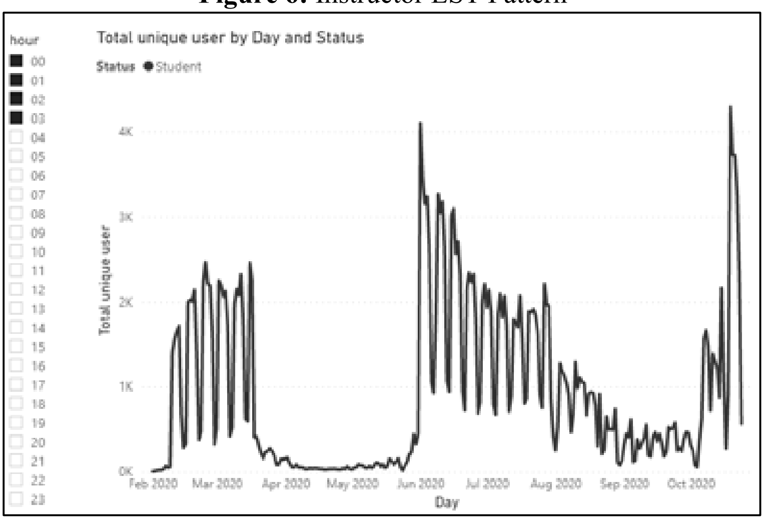

Figure 7: Student EST Pattern

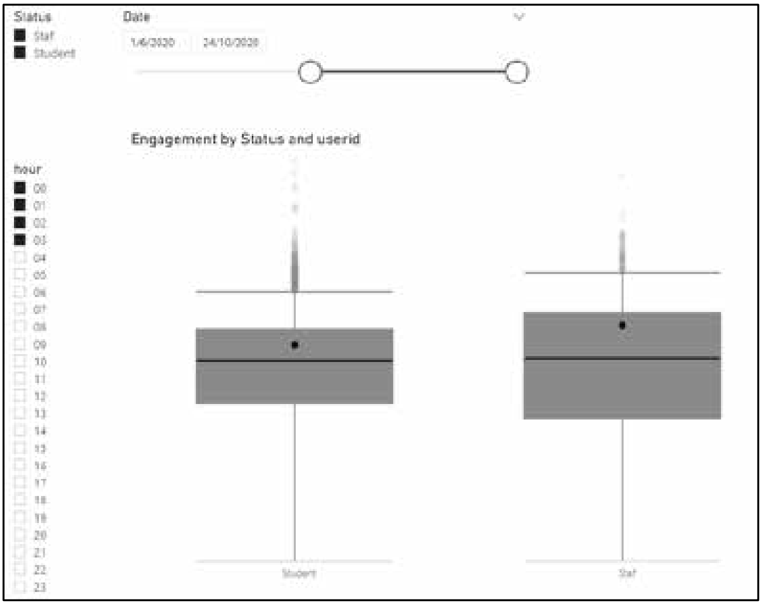

Figure 8: Outliers detection in box-plot visualization

Both figures show there are users who are still engaged in LMS during typical sleep time. This analysis however did not indicate the same user who may continuously experience EST. To gain the insight of each individual user, this study analyses the dataset by using box-plot visualisation to visualise the outliers, as shown in Figure 8. It shows the anomaly or outliers that represent EST from the dataset based on the potential indicators earlier. The analysis covers the data from June 2020, between 12 AM to 3 AM and segment to type of user.

Figure 8 shows that there are outliers (sampled users) from analysis of screen time frequency segmented into type of user. The findings show that there were students and instructors who experienced EST during the duration of lockdown or pandemic. To indicate the number of affected users, this study quantifies the outliers and summarises it in Table 3. There are more than 10% of instructors and students who are classified as outliers or potential EST users. This result has answered RQ1, which is, it is feasible that EST can be modelled with EDM.

Table 3: Outliers as EST indicator

Paramater	Instructor	Student
Total sampled user	922	14359
Total records	11,511,626	21,040,557
Minimum engagement duration (minutes)	1	1
Median engagement duration (minutes)	203	361
Average engagement duration (minutes)	988.49	887.77
Maximum engagement duration (minutes)	456187	6374153
Number of user at Quartile 1 (Q1)	60	107
Number of user at Quartile 3 (Q3)	680	637
Interquartile range (IQR)	620	530
Lower Bound	-870	-688
Upper Bound	990	902
Number of user categorized as outliers	**148**	**1591**
% EST user	16%	11%

To answer RQ2, the aspect of EST is very much close to the theory of personalised learning. In other words, any educational activities should consider EST in attaining the educational outcomes. Experiencing care is also crucial for student success in higher education, especially in the stressful situation during pandemic. These results are similar with previous study (Majumdar et al., 2020), which indicates exposure screen time among student and office workers of India during pandemic has increased significantly. EST indication is important for instructors to perform their duty in a safe and healthy manner, which is related with occupational safety and health. Therefore, proper monitoring of EST in LMS is critical and this can be done with EDM modelling contributed from this study.

CONCLUSION

The findings from this study suggest that there is a feasible way on how EST in LMS can be measured quantitatively without carrying a subjective survey-based approach. This study shades new directions on how institutional policy on student and staff digital well-being can be introduced to mitigate potential risks or adverse effects of EST in the long term. Further research on policy, quality standard and guidelines for healthy and sustainable practice of online learning is critical towards sustainable development goals of higher education.

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