Modeling Excessive Screen Time Indicator in Learning Management System During COVID-19 Pandemic

Aziman Abdullah[1*]

[1]Faculty of Computing, College of Computing & Applied Sciences, Universiti Malaysia Pahang, 26600 Pekan, Pahang, Malaysia

[*]Corresponding author's email: aziman@ump.edu.my

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 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 scholar on modeling EST based on actual engagement in online learning at higher education. Therefore, this study adopted educational data mining (EDM) with box-plot visualization to identify outliers as indicator of excessive in user's screen time. The findings show there are more than 10% of student and instructor who are classified EST user. To conclude, this study has shaded a light for higher education on the call for new policy, quality standard and guideline how healthy online learning engagement should be effectively monitored to mitigate associated risks with EST towards sustainable development goals.

Keywords: *screen time; online learning; pandemic*

1. INTRODUCTION

The COVID-19 pandemic has forced all institution globally to cope with a new normal by adopting a full online learning through LMS to practice social distancing. For most student who stay remotely or at home during 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[1] on the limit of screen time for children published by World Health Organisation (WHO), the limit for adults is still unclear. Many studies[2]–[5] on screen time in higher education adopted self-reporting approach such as survey. Not only the survey-based approach limits the accuracy of the actual screen time of the LMS users, but the approach also induces information latency where critical information received too late for decision to be made, especially when the information is critical and associate with the risk aspects on health. While many scholars have approached EDM in learning analytics domain, there is lack of attention on screen time modelling with EDM in literatures.

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 feasible to model EST with EDM approach?
RQ2: What is potential impact of EST on higher education?

2. METHODOLOGY

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

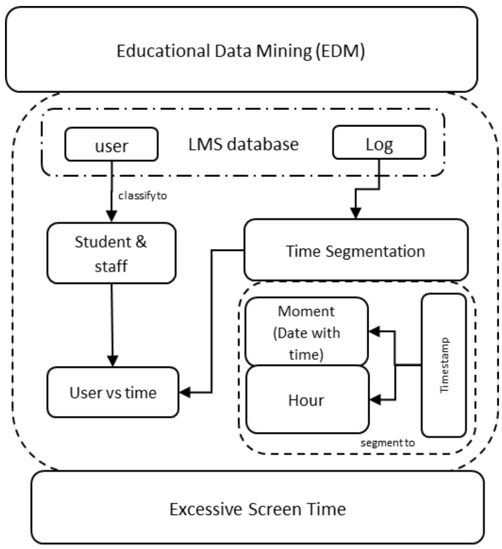

Figure 1 Research Methodology

The LMS log keep the timestamp and user ID. Based on user ID, the researcher able to classify them as student or staff based on their email address pattern. Their email address however not been disclosed in the analysis in the study. The timestamp data allow researcher to indicate the moment of engagement occurred for every user at every interaction. This data then been processed to extract the date and time of the engagement occurred as screen time metric. It means, each user is quantified based on the every minute they engaged in LMS. Based on these metric, the data are been analyzed by using frequency of engagement for the whole duration of dataset which is from 1st Feb 2020 to 24th Oct 2020. The anomaly or outliers from the analysis then considered as EST. The box-plot visualization is a technique that been used to identify excessive indicator represented as outliers or anomaly from the dataset.

3. RESULTS AND DISCUSSION

The results of EST for student and staff category on online learning engagement in LMS are presented in Figure 2. It shows the anomality or outliers that represent EST from the engagement dataset.

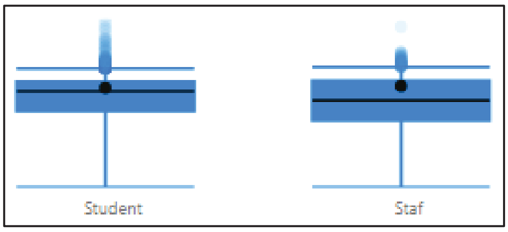

Figure 2 Outliers detection in box-plot visualization

Figure 2 shows that there are outliers (sampled users) from analysis of engagement frequency segmented into type of user. The findings show that there were student and instructor who experienced EST during the duration of lockdown or pandemic. To indicate the number of affected users, this study quantifies the outliers and summarizes in Table 2. There are more than 10% of instructor and student who classified as outliers or potential EST user. This result has answered RQ1 which is, it is feasible that EST can be modelled with EDM.

Table 2. Outliers as EST indicator

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

To answer RQ2, the aspect of EST is very much close on the theory of personalized learning. In other words, online learning engagement should also concern about user's wellbeing apart of attaining the educational outcomes. Experiencing of being care is also crucial for student success in higher education, especially in the stressful situation during pandemic. This results are similar with previous study[2] which indicates exposure screen time among student and office workers of India during pandemic has increased significantly. EST indication is important for instructor to perform their duty in safe and healthy manner which is relate with occupational safety and health. Therefore, proper monitoring of online user engagement in LMS on EST is critical and this can be done with EDM modelling contributed from this study.

4. CONCLUSION

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

ACKNOWLEDGEMENT

This work was supported by the Universiti Malaysia Pahang internal research grant RDU1903116.

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