Screen Time in Learning Management System as Student Learning Time Indicators for Academic Quality Assurance

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Abstract: This study explores the potential of using screen time data in learning management systems (LMS) to estimate student learning time (SLT) and validate the credit value of courses. Gathering comprehensive data on actual student learning time is difficult, so this study uses LMS Moodle logs from a computer programming course with 490 students over 16 weeks to estimate SLT. The data was segmented into a minute for each record and total duration was calculated for each student on a weekly basis. The study found variations in SLT on a weekly basis and identified that the number of students who engaged with the LMS after midnight varied according to week, possibly due to assessment deadlines. These findings suggest that screen time data in LMS can be utilized for data-driven decision making for academic quality assurance in higher education. This study can help policy makers and academic institutions to make more informed decisions and promote personalized learning experiences.

Keywords: Screen Time, Student Learning Time, LMS, Quality Assurance

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Introduction

Student learning time (SLT) is a critical aspect of higher education, as it is a key indicator of the amount of time that students 'expected' to spend to engage in learning activities that credited for their qualification. In practice, SLT has been determined based on notional learning hour which include all learning activities associated to achieve the learning outcomes. However, very few research and practice address the validation aspect of the credits due to the difficulty in gathering a comprehensive actual data of SLT in a course. Besides, it is important to note that the actual amount of time that a learner spends on a particular activity may vary depending on factors such as prior knowledge, learning style, and individual pace of learning. Getting data or responses from each student on how much they spent their actual time for learning in each course they enrolled through self-report or survey seems impractical. This is due to inaccuracy and incompleteness of the data to represent the whole student in individual manner. Nevertheless, many scholars have research using user engagement data or screen time data in learning management system (LMS) towards quality education(Zanjani, 2016). Therefore, this paper aims to investigate the feasibility of measuring SLT based on screen time data in LMS as potential new indicator for academic quality assurance in higher education.

Literature Review

Student Learning Time

Student learning time (SLT) refers to the amount of time a student spends on academic activities such as attending lectures, participating in discussions, completing assignments, and studying for exams. SLT is a theoretical estimation based on the concept of notional learning time. Notional learning hours are often used to calculate the credit value of a course or module, and they can also be used to plan and schedule training activities. It was based on estimated value by the experts or higher education providers during the curriculum design stage. In the context of Malaysian higher education, SLT has been described as "*the amount of time that a student is expected to spend on the learning-teaching activities, including assessment to achieve specified learning outcomes*." (Malaysian Qualification Agency, 2008).

A literature(Mohamed, 2016) that proposed the SLT model indicates there are four major operational components namely as official contact hours, guided learning time, self-study time and assessment time as shown in Figure *4*. The model also categorized the the components as "*Guided Learning Time*" and "*Independent Learning Time*". The "*Guided Learning Time*" might be used for face to face (F2F) or none face to face (NF2F) interactions or learning activities, while "*Independent Learning Time*" is typically used with NF2F learning activities.

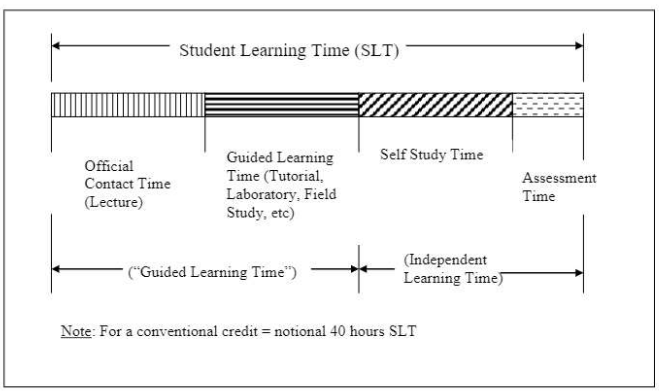

Figure 4 SLT Model (Mohamed, 2016)

Basically, the F2F is conducted based on the designated schedule can be practically quantified based on the duration of 'contact hours' either in classroom or online meetings normally with the presence of instructor. The amount of time for F2F sessions can be expected is the same for each learner. While for NF2F, where it been conducted without the presence of instructor, the amount of time student spend may varies due to various factors such as complexity of learning materials, learning style, personal disabilities, conduciveness of the learning environment as well as student's personal commitment and responsibilities. Nevertheless, the total of SLT from

F2F and NF2F were used as indicators to determine the credit hours of the course.

In the Code of Practice for Programme Accreditation (COPPA) of higher education in Malaysia, SLT can be categorized as F2F and NF2F as shown in Figure 5. The NF2F of SLT is very significant for higher education since higher education is distinguished from general and secondary education by its focus on independent learning(Thompson, Pawson, & Evans, 2021). Research has shown that higher levels of NF2F SLT or independent learning are associated with better academic performance and higher rates of student retention (Kuh et al., 2008). Additionally, SLT has been linked to the development of key skills and competencies, such as critical thinking, problem-solving, and information literacy (Pascarella & Terenzini, 2005). The issue is, how to validate the NF2F SLT in term of accuracy and what are the variation of actual NF2F SLT in a course?

Distribution of Student Learning Time (SLT):

Course Content Outline	CLO*	Learning and Teaching Activities						Total SLT
		Guided Learning (F2F)				Guided Learning (NF2F) e.g. e-Learning	Independent Learning (NF2F)	
		L	T	P	O			
1.								
2.								
3.								
4.								

Continuous Assessment	Percentage (%)	F2F	Independent Learning (NF2F)	Total SLT
1.				
2.				

Final Assessment	Percentage (%)	F2F	Independent Learning (NF2F)	Total SLT
1.				
2.				

GRAND TOTAL SLT	

L = Lecture, T = Tutorial, P = Practical, O = Others, F2F = Face to Face, NF2F = Non-Face to Face
*Indicate the CLO based on the CLO's numbering in Item 8.

Figure 5 SLT Calculation in COPPA (Malaysian Qualification Agency, 2008)

Learning Management System (LMS) in Higher Education

Learning Management System (LMS) is a type of information system or software that designed to manage, deliver and monitor online and offline educational courses and training programs. It typically involves the use of internet or digital platforms and can come in various forms, such as online courses, virtual classrooms, educational software, and mobile apps. Its features typically include user registration, course creation and management, tracking of progress, grading and assessment, and communication tools. LMS offers learners the convenience and flexibility of accessing educational materials and interacting with instructors and peers at any time and from any location(Dimitrova, Mimirinis, & Murphy, 2004). Additionally, learners can personalize their learning experience by choosing the style and pace of their learning(Dhaiouir, Ezziyyani, & Khaldi, 2022). As a result, LMS has gained popularity in recent years and is increasingly being adopted by schools, universities, and organizations for educational programs and training. The recent global COVID-19 pandemic also has become a significant factor for global higher education to adopt LMS for their educational productivity(Wang, Li, Malik, & Anwar, 2022). With these benefits, LMS can be a significant technology for e-learning implementation to achieve the United Nation Sustainable Development Goals(Ghanem, 2020) as illustrated in Figure 6.

Figure 6. E-learning impacts on SDG (Ghanem, 2020)

In research, LMS holds great importance as it contains valuable data regarding the users' interactions with the system. This educational data known as system log is a valuable resource for scholars as it provides insights into human behavior, particularly related to the complexity of future learning and future competences in higher education(Kleimola & Leppisaari, 2022). Apart of that, these data can provide valuable information to administrators and policymakers about resource allocation and program evaluation using learning analytics(Hou, Lee, Chen, & Wu, 2023). Adopting learning analytics from LMS data oriented to academic quality assurance can bring about numerous advantages for educational institutions. For instance, instructors and administrators can receive immediate feedback through learning analytics, enabling them to pinpoint areas where students might be facing difficulties and modify their teaching approaches accordingly. This can enhance student achievement and, in turn, enhance the overall excellence of the educational program.

The crucial aspect linking learning analytics and SLT is the amount of time spent student engage in LMS. In LMS, the actual moment and duration of SLT either by guided learning or independent learning can be indicate by their screen time. In addition, learning analytics can also assist in identifying patterns and trends in student behavior, such as their level of engagement and participation in online discussions and assignments. By analyzing this data, instructors and administrators can gain valuable insights into how students are interacting with the course material and with each other, which can help them make informed decisions about how to improve the learning experience. Furthermore, learning analytics can also support decision-making related to resource allocation, as institutions can use the data to determine which courses and programs are most effective and where additional support may be needed. Overall, learning analytics provides a powerful tool for improving the quality and effectiveness of education by leveraging the rich data generated through LMS.

Screen Time

Screen time (ST) is a concept that referring to the amount of time spent using a device with a screen such as a smartphone, computer, television or video game console. ST also can be determine based on digital engagement that include the context of time and object that user engage with in the LMS. In practice, the timestamp data play a crucial role to determine the moment and duration of ST in any information system like LMS. Some scholars refer this data as digital footprint(Pavlenko, Barykin, & Dadteev, 2021). Many literatures highlight the negative effects especially on excessive screen time (EST) on students' academic performance, physical health, and overall well-being. EST can lead to a sedentary lifestyle, which in turn can increase the risk of obesity(Benaich et al., 2021) and other health issues(Tang, Werner-Seidler, Torok, Mackinnon, & Christensen, 2021). Additionally, too much ST can negatively impact students' sleep patterns(Hjetland, Skogen, Hysing, & Sivertsen, 2021; Muhammad, Hussain, & Adnan, 2021), which can affect their ability to learn and retain information.

While many scholars associate screen time with negative impacts, there is a potential benefit of screen time in the context of academic quality assurance. Some scholars assess the ST by using self-report or survey based approach(Vizcaino, Buman, Desroches, & Wharton, 2019). Although self-reported is a well-established and commonly adopted in wide area of research studies, a study proves that self-reports can overestimated the actual use of ST(Hodes & Thomas, 2021). ST can be quantified by using specific tools or pre-designed mechanism of information system. In the context of data quality, there are ST software tools that have been developed that aim to manage the user screen time with objective manner(Kristensen et al., 2022). For example, the built-in ST software tools in mobile operating systems that assisting user to manage and monitor their screen time with smartphone as shown by Figure 7. Since LMS also stored the user engagement data or screen time data, there is potential how these data can be further utilized to quantify objectively SLT similarly from the existing ST software tools.

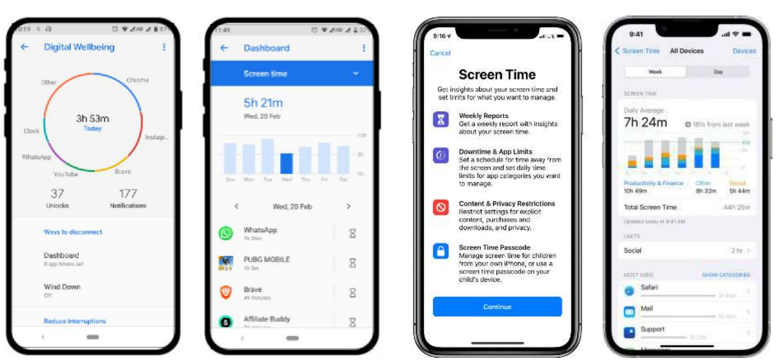

Figure 7. Screen Time Control in Android and iOS Mobile Operating System

Method

This study aims to quantify in objective manner the SLT based on ST in LMS. Research questions of the study are as follows:

- How to visualize the SLT of one individual student?
- How to visualize the SLT of the whole student?

To answer the research questions, information about the research model, data collection and data analysis have been given.

Research model

This study adopts the learning analytics approach for acquiring the collected data from LMS. The following are the research model adopted in this study: -

1. The dataset was acquired from the log report that generated from LMS based on Moodle for Computer Programming course enrolled by 493 students. There are 9 parameters stored in the Moodle log as shown in Figure 8 and it can be downloaded into various file formats such as Comma Separated Values (.csv), Microsoft Excel (.xlsx) or HTML table.

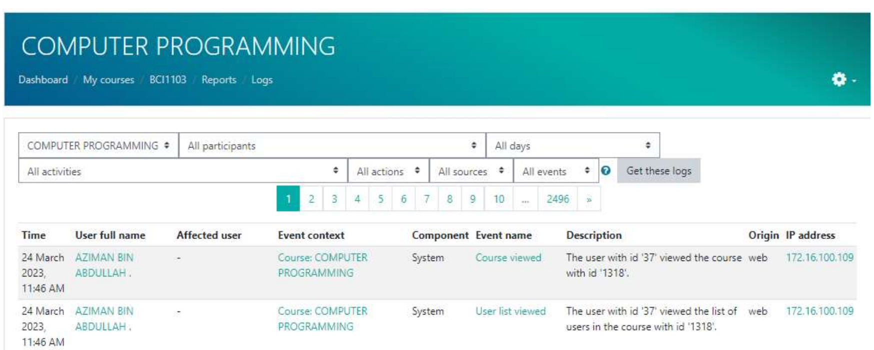

Figure 8. Moodle LMS Log

2. Download the dataset in Microsoft Excel (.xlsx) format since the analysis will be done in Microsoft Excel software. The size file is subject to the total record of the log in the course. In principle, the bigger is the class size or number of student, the larger the size of the log or the size file to save all the record. However, the small class size with highly active online learning activities may result with large size file of the log.
3. Open the file in Microsoft Excel and transform the data of the date into 6 new parameters namely year, week, time, hour, minutes and day of the week as shown in Figure *9*. This transformation can be done

by using specific Excel function and formula.

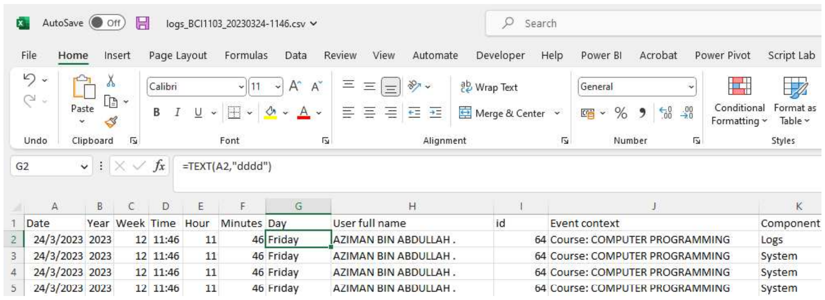

Figure 9. Transformed Dataset in Microsoft Excel

4. Analyze the dataset with Microsoft Excel by using PivotTable to calculate the total number of ST to represent SLT.

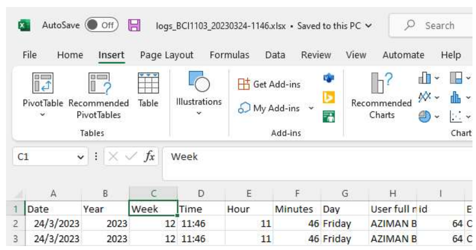

Figure 10. Data Analysis with PivotTable

5. Based on the pivoted dataset, then many analysis can be used to explore the pattern of SLT by using various visualization techniques available in Excel.

Results

There are 24955 logs were retrieved from the LMS. The description of the study population is illustrated in Table 3.

Table 3. Dataset description

Faculty	Enrolled students
Faculty Of Chemical And Process Engineering Technology	86
Faculty Of Civil Engineering Technology	100
Faculty Of Electrical & Electronic Engineering Technology	57
Faculty Of Industrial Sciences & Technology	79
Faculty Of Manufacturing And Mechatronic Engineering Technology	37
Faculty Of Mechanical And Automotive Engineering Technology	131
Total	490

The findings from this study are organized based on the research questions as follows: -

1. How to visualize the SLT of one individual student?

Since the student's timetable has been organized in a weekly basis, the analysis of SLT or ST should be view in a weekly basis. Data that represents the context of time should adopt the temporal visualization and we found bar chart similarly with the existing ST software tools can be effective visualizations to visualize SLT of one individual student. Figure 11 shows the fluctuation of ST frequency for each week of the highest ST overall sample. To explore the difference of the other student who are moderately engaged in LMS, this study uses another sample based on the median value of overall ST per semester as shown in Figure 12.

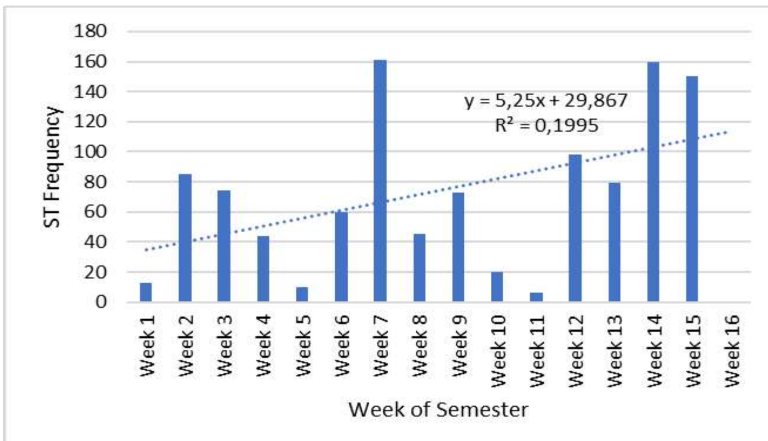

Figure 11. SLT Trend Per Week of Highest ST

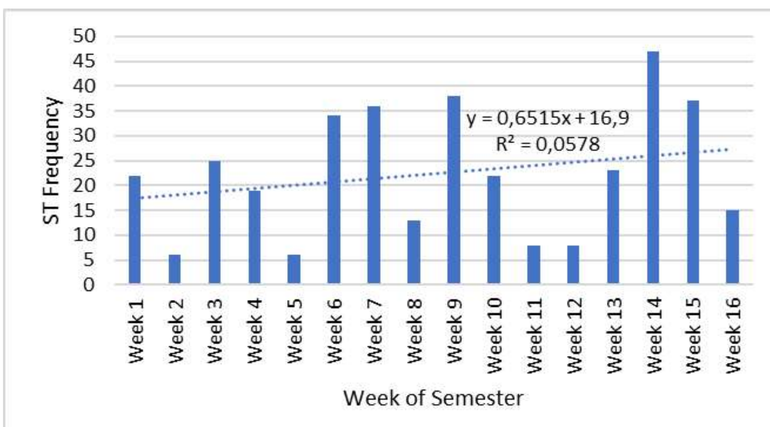

Figure 12. SLT Trend Per Week of Moderate ST

2. How to visualize the SLT of the whole student?

Based on the findings in Figure 11 and Figure 12, it is clear that the weekly SLT frequency pattern of two different student is varied. To visualize the pattern of the whole population with the size of 493 students, obviously the analysis and visualization for one student with simple linear regression is not appropriate. Therefore, this study attempts to visualize the SLT pattern of the whole student by using distribution visualization. There are two distribution visualization techniques been adopted which are heatmap matrix and boxplot. The heatmap matrix used to indicate the distribution of actual number of students on contextual SLT according to the time clock and week of semester as shown in Figure 13. While Figure 14 displays a boxplot chart that can be used to further examine the weekly SLT pattern of all students over a semester.

Hour	Week															
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
0	32	24	62	26	23	47	156	41	29	15	23	29	77	58	157	26
1	13	13	31	12	19	31	72	9	13	8	15	13	45	40	94	14
2	4	2	13	7	7	18	45	7	10	2	3	6	32	25	67	12
3	6	2	8	7	6	9	30	4	6	3	6	5	17	11	38	7
4	1	1	3	3	2	9	17	2	2	3	3	1	1	3	36	11
5	4	3	4	3		3	17	4	2	3	5		7	2	19	6
6	19	4	7	8	1	6	16	5	3	4	1	1	6	5	15	3
7	30	16	29	20	8	18	37	6	18	4	2	9	5	18	22	11
8	66	82	83	57	19	98	123	14	68	39	15	81	71	85	27	13
9	68	41	81	80	26	92	99	15	94	37	17	32	42	46	43	13
10	103	88	140	102	52	125	149	82	110	80	72	78	78	66	51	26
11	91	64	143	89	57	103	126	104	75	55	36	49	75	74	79	35
12	146	106	217	139	140	161	216	100	154	119	102	145	159	129	78	26
13	76	95	134	92	45	71	146	70	116	78	46	52	95	133	76	34
14	77	71	138	90	64	106	156	50	122	80	47	62	72	116	110	39
15	76	60	130	91	62	94	149	46	93	38	37	44	85	76	140	35
16	47	41	131	96	85	100	182	52	106	50	29	63	91	92	127	33
17	33	36	81	54	56	80	137	43	47	39	23	22	59	89	118	47
18	30	17	67	41	17	89	123	25	34	31	12	23	55	87	111	24
19	42	25	95	40	27	75	168	38	43	22	20	26	50	376	116	20
20	65	85	147	60	34	120	180	39	65	40	27	82	142	387	184	39
21	69	71	169	73	39	104	213	36	92	32	42	35	155	379	199	47
22	59	45	151	59	44	103	219	40	60	25	33	39	134	382	216	47
23	49	47	123	44	29	108	235	48	32	28	34	40	98	88	252	41

Figure 13. Total Student with contextual SLT every week

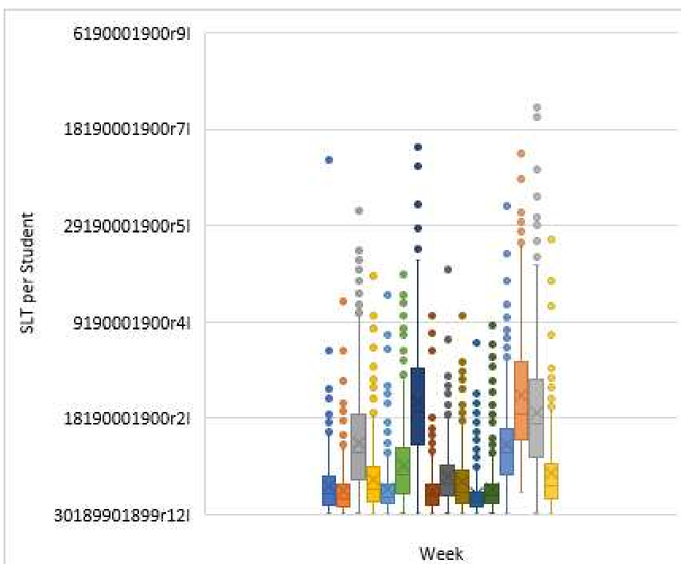

Figure 14. Weekly SLT Trend for Whole Student

Discussion

Based on the Figure 11 and Figure 12, both samples indicate the increasing trend of ST throughout the semester when the data is regressed linearly. The value of coefficient of determination (r^2) shows that the amount of SLT can be explained by the number of weeks in a semester. It seems the variation of the r^2 score can be used to quantify the SLT pattern of student on weekly basis for a semester in individual manner. This analysis is potential to be used for data-driven decision making for students and instructors indicating their committed time for learning or SLT that can be translated from ST data. This is critical for higher education institution to promote and monitor personalized learning experiences(Bernacki, Greene, & Lobczowski, 2021). This type of analysis could be used to promote personalized learning experiences and monitor student progress in higher education institutions. By using ST data to track SLT, instructors and students can identify patterns and trends in their study habits and use this information to develop more effective time management strategies. For example, students who consistently spend more time on their coursework earlier in the semester may be better prepared for exams and assignments later on, while students who consistently procrastinate may benefit from additional support and resources to help them stay on track. Furthermore, the potential for data-driven decision making based on ST data has important implications for the e-learning industry. Personalization is becoming increasingly important in next-generation LMS (Kipp, 2018), and the ability to track and analyze SLT can be a valuable tool for instructors and developers looking to create more personalized and effective learning experiences for students. By utilizing this data to track and analyze student study habits, instructors and students can work together to promote academic success and personal growth.

There are many students were spending time in the LMS and staying late after midnight referring to Figure 13. One possibility is that the students were highly motivated and were using the LMS to supplement their learning. They may be working on assignments, studying for exams, or reviewing course materials to ensure that they fully understand the material especially when it is near to the deadlines or exam dates. In this case, spending extra time in the LMS could be a sign of their dedication to their studies and a desire to excel academically. However, there may be other reasons why students are staying up late in the LMS. For example, they may be struggling with the material and feel that they need to put in extra effort to catch up. They may also be dealing with personal or family issues that make it difficult for them to study during regular hours. In some cases, students may simply be procrastinating and putting off their work until the last minute(Reinecke et al., 2018). Regardless of the reason for their behavior, it is important for educators to be aware of the situation and provide support to students as needed.

Figure 11 suggests that there are some outliers in the student's weekly SLT as well as a high degree of variation in the average SLT per week for the entire semester. Outliers refer to values that are significantly higher or lower than the majority of the data points. In the case of Figure 11, this means that there are some students who are spending much more on self-regulated learning activities than the average student. This could be indicative of a variety of factors, such as differences in learning styles, motivation, or personal circumstances. Meanwhile, the high variation in the average SLT per week for the entire semester could suggest that students are having difficulty maintaining consistent study habits over the course of the semester. This could be due to several factors, such as changes in workload, stress levels, or competing priorities over the time.

By identifying these patterns through Figure 11, educators can better understand the challenges that students are facing and develop targeted interventions and support strategies to help students overcome these obstacles. For example, educators could offer additional resources or support to help struggling students catch up or develop more effective study habits. They could also encourage students to reflect on their learning habits and identify areas for improvement. Overall, the insights gained from Figure 11 can inform data-driven decision making that ultimately leads to more effective and personalized support for students.

The potential impacts of utilizing screen time data in LMS as SLT indicators for academic quality assurance are significant across several sectors as follow:

1. Society: Utilizing LMS can be an effective strategy to enhance accessibility to education, advance learning achievements, and promote lifelong learning and collaboration, particularly for individuals from marginalized groups like people with disabilities or physical barriers. The research provides insights on how to create a more supportive and emphatic learning environment for such individuals by utilizing data-driven decision making to gain a better understanding of their actual learning experience within the course.
2. Academia: This approach has the potential to revolutionize how student learning time is measured, verified, and used to design, develop, and deliver academic programs. It could lead to a more accurate, objective and comprehensive understanding of the time students actually spend on learning activities, and therefore, enable institutions to ensure that students are meeting the necessary credit value of a course. It could also facilitate personalized learning experiences for students and provide instructors with insights on how to improve teaching practices.
3. Government: The use of screen time data in LMS could help regulators and accrediting bodies to verify the quality of academic programs and ensure they meet the necessary standards. This approach could also provide policymakers with valuable insights into the effectiveness of online learning environments and how they can support the expansion of digital learning opportunities.
4. Industry: This approach could lead to the development of better Learning Management Systems that are designed to collect and analyze screen time data and provide personalized learning experiences for learner either in education or corporate training. It could also foster the development of data-driven decision-making processes that can improve the overall quality of academic programs and contribute to better workforce outcomes.
5. Environmental: The use of screen time data in LMS could reduce the need for paper-based assessments and feedback, which would have a positive impact on the environment by reducing waste and resource consumption. This approach could also facilitate distance learning opportunities, which could reduce the need for students and instructors to travel, leading to reduced carbon emissions and a smaller environmental footprint.

Conclusion

The potential contribution of data-driven decision making based on student data from the LMS can be significant in supporting students who are spending time in the LMS and staying up late after midnight. By analyzing student data, educators can gain insights into how students are using the LMS and identify patterns in their behavior, such as which activities they are spending the most time on and when they are most active in the LMS. This information can then be used to inform interventions and support strategies that are tailored to the needs of individual students. For example, if educators notice that a particular student is spending a lot of time on a particular activity but is not making progress, they may offer additional resources or support to help them understand the material better. In addition, by using SLT data to inform decision making, educators can develop more effective strategies for promoting healthy study habits and time management skills(Cao, Zhang, Chen, & Shu, 2022). They can identify which interventions are most effective for different types of students and adjust their approach accordingly. As digital learning has become an integral part of academic operations in many institutions, our findings can provide insight for policymakers and academics on how to use screen time data from LMS for data-driven decision making to ensure academic quality assurance in higher education.

Recommendations

Future research could build on the findings from this study and explore additional questions related to SLT in higher education. Here are some potential areas for further investigation:

1. Factors influencing SLT: This study identified that there is high variation in SLT among students. Future research could examine the factors that contribute to this variation, such as differences in learning styles, motivation, or personal circumstances. Understanding these factors could help educators develop targeted interventions and support strategies that are tailored to the needs of individual students.

2. Relationship between SLT and academic performance: This study did not examine the relationship between SLT and academic performance. Future research could explore whether there is a correlation between SLT and grades or other measures of academic success. This could help educators better understand how SLT relates to overall student achievement and inform strategies for promoting academic success.

3. Relationship between SLT and digital well-being: As students spend more time engaging with digital technologies, it is important to understand how this affects their well-being and how it may impact their ability to engage in effective self-regulated learning. Policy makers could work with educators and experts to develop guidelines for healthy digital use that can be shared with students and families.

4. Longitudinal analysis of SLT: This study examined SLT over one course of a single semester. Future research could conduct a longitudinal analysis of SLT over a longer period of time to better understand how students' study habits evolve over time and whether there are changes in SLT over the course of a student's academic career.

5. Comparison of SLT across courses for the whole curriculum: This study examined SLT among students in a

single course. Future research could compare SLT across different courses and student's level to explore whether there are differences in study habits and self-regulation strategies across courses.

6. Impact of support interventions on SLT: Finally, future research could examine the impact of support interventions on SLT. For example, researchers could explore whether offering additional resources or support to struggling students leads to an increase in SLT and improved academic performance. Understanding the effectiveness of different support strategies could help educators develop more effective and targeted interventions to support student success.

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