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Evaluating Student Activity and Learning on Moodle: A Data-Driven Analysis and Insights of Usage Reports

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ABSTRACT

Learning Management Systems (LMS) are extensively utilized to enhance teaching and learning in higher education institutions. These platforms provide invaluable insights into users' usage data and behavior within the online environment. Therefore, evaluating users' activity on these platforms is essential to maximize their effectiveness. This study aims to evaluate usage reports and engagement patterns and analyze online student learning activity using Moodle's tracking features. To achieve this, statistical and visualization techniques were employed to analyze student data from a year-long module delivered in a blended mode during the first semester at a South African university. The study utilized LMS log data to evaluate students' and instructors' usage patterns and engagement levels on the online platform, focusing on module-related activities. The data mining analysis revealed that LMS usage was significantly higher when students were on campus during the first semester and relatively lower when off-campus or in residence. In addition, no significant differences were observed in the type of LMS tools used or module activities across the eight months of the first semester. In conclusion, this data-driven approach and its findings underscore the importance of monitoring LMS activity.

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INTRODUCTION

In recent years, we have witnessed the widespread adoption of Learning Management Systems (LMS), which make large amounts of educational data accessible for learning analytics (Maluleke, 2024). During the outbreak of COVID-19, LMS played a critical in education and has increased by leaps and bounds. Traditionally, LMSs complement face-to-face learning, whereby instructors only upload lecture-related content, conduct quizzes, and facilitate assignment submissions (Hamid et al., 2022). As Learning Management Systems (LMS) like Moodle become integral to higher education, they offer valuable tools for tracking and understanding student behavior in online environments (Kumar & Sharma, 2016). Moodle's built-in tracking features provide detailed logs of student interactions, including logins, resource views, participation in forums, and assignment submissions (Gamage et al., 2022). These logs can serve as a rich source of data for examining patterns of engagement, which are critical for assessing the effectiveness of online learning activities (Martin et al., 2016). As such, the implementation of technology in the field of learning has evolved traditional learning perspectives. As a platform for online learning, LMSs create a virtual world that connects educators to learners, thereby changing learning methods. The increasing use of data analytics in education allows institutions to make informed decisions about improving course design and student support strategies (Dawson & Siemens, 2014). Learning analytics measures, collects, and analzses learner-related data to understand and optimize learning. Since learning occurs over time, the effects of time on learning have been explored for a long time (Raj & Renumol, 2024). In his seminal study, Carroll explicitly distinguished between time-on-task and time-off-task as the time devoted to learning and the time engaged in activities other than learning, forming the elapsed time (Rotelli & Monreale, 2022; Carroll, 1963). In learning analytics research, temporal analysis has emerged as a crucial study area, demonstrating its relevance in understanding and improving student outcomes (Lang et al., 2017). One of the critical aspects of temporal analysis is capturing time-on-task, which serves as a valuable proxy for modeling learning behavior. Researchers can gain insights into their engagement levels, cognitive processes, and overall learning patterns by analyzing learners' time on specific tasks or activities. This approach has been the subject of numerous investigations, focusing on its potential to predict student performance, identify at-risk learners, and develop early intervention strategies to prevent dropout (Rotelli & Monreale, 2022). Additionally, temporal data can help tailor personalized learning experiences, providing educators with actionable insights to adjust instructional approaches and optimize student success. As learning analytics continues to evolve, temporal analysis is becoming increasingly integral to adaptive learning systems and data-driven educational decision-making. Moodle’s tracking capabilities:This study will analyze how students engage with course materials and identify factors contributing to higher levels of participation in the LMS. This study uses Moodle's tracking features to focus on usage reports, engagement patterns, and online student learning activity analysis (Zhang et al., 2020). The insights gained will provide educators with actionable information to enhance the student learning experience and improve outcomes in online learning environments.

Learning Management Systems (LMS) are software applications for delivering and managing online education. (Rahman et al., 2019; Bradley, 2021). LMS facilitates teaching and learning processes in higher education, offering benefits such as documentation, tracking, and reporting of educational courses (Rahman et al., 2019). These systems have evolved since their introduction in the late 1990s and are now widely used in distance learning, blended learning, and flipped classrooms. (Tomei et al., 2024). LMS can improve student learning outcomes, engagement, and satisfaction, although the effects depend on factors like instruction type and student engagement level (Elegbeleye et al., 2022; Ramansyah et al., 2024). Learning Management Systems (LMS), such as Moodle, have become indispensable tools in higher education, offering a comprehensive platform for content delivery, coursework management, and facilitating meaningful interaction between students and educators (Cabero-Almenara et al., 2019).

As the shift towards digital and blended learning environments continues to grow, evaluating student activity and learning patterns within these systems becomes increasingly essential. Such evaluation is critical for optimizing educational outcomes, as it helps institutions and educators tailor their approaches to meet student needs more effectively (Tatineni, 2020). A key method for gaining insights into student behavior within LMS environments is the analysis of usage reports, which provide detailed logs of various learner activities. These reports track crucial data points such as login frequency, time spent on specific tasks, the content accessed, and participation in discussion forums (Uhlenhake, 2019). By analyzing these metrics, educators can identify engagement trends, monitor how students interact with the material, and pinpoint areas where learners may require additional support. Furthermore, understanding student behavior through usage reports enables institutions to implement data-driven strategies that enhance learning experiences (Liu et al., 2017). For example, students who log in frequently and spend more time on coursework are often better positioned to succeed. At the same time, those with minimal activity may be at risk of falling behind. Such insights allow for early identification of at-risk students, enabling timely interventions to improve retention, boost performance, and ensure more equitable learning outcomes (Macfarlane, 2021). This way, LMS usage reports support student success and inform continuous course design and instructional strategy improvement.

As an open-source Learning Management System (LMS), Moodle provides a comprehensive set of tools for tracking and reporting student activities, enabling educators to gain valuable insights into how students engage with course materials. These tools generate usage reports that include detailed logs of user interactions, time-on-task data, and participation metrics, offering a rich data set for analyzing learning behaviors. Research has consistently shown that these data-driven insights are instrumental in evaluating student engagement, predicting academic outcomes, and fostering more personalized learning experiences (Rebeca et al., 2020). Using the wealth of data available in Moodle's usage reports, educators can monitor student performance in real time, allowing for a dynamic understanding of how students interact with content. This real-time monitoring is handy for identifying learners who may fall behind, show disengagement, or struggle with specific concepts. With this information, educators can implement timely interventions to address these issues, such as offering additional support, adjusting course content, or providing personalized feedback (Shoaib et al., 2024; Mbaleki et al., 2023). Moreover, the data can be used to uncover patterns and trends in student behavior, helping institutions make informed decisions about instructional strategies and course design. Activity tracking and predictive analytics allow for more effective teaching practices and improved student retention, ensuring educators are better equipped to support learners on their academic journey.

Several studies have highlighted the correlation between student activity in Moodle and academic performance. For instance, temporal analysis of student engagement—examining when and how frequently students interact with course materials has been shown to predict overall success in online courses (Soffer & Cohen, 2019). Time-on-task is widely recognized as a key indicator of student effort and engagement. Research suggests that students who interact more with learning materials are more likely to achieve better academic outcomes (You, 2016). This correlation highlights the importance of tracking student activity and understanding the context and quality of these interactions within the Learning Management System (LMS) (Burušić et al., 2021). By analyzing time spent on tasks alongside other behavioral metrics, educators can gain deeper insights into student engagement, learning patterns, and areas where students may need additional support. Furthermore, time-on-task can help identify at-risk learners who may fall behind, enabling timely interventions to improve retention and performance. Thus, tracking and interpreting time-on-task data is crucial in enhancing the learning experience and fostering academic success.

In addition to retrospective evaluations, usage data from Moodle can be used for predictive modeling. Learning analytics tools have evolved to predict student success based on patterns in activity data. For example, the frequency of logins, the amount of time spent on specific tasks, and participation in online discussions can be used to predict final grades with considerable accuracy. By applying machine learning algorithms to Moodle's usage reports, educators can identify at-risk students early in the course and implement strategies to improve retention and performance. One study by Perić Prkosovački (2024) demonstrated that the early identification of less engaged students with course content through LMS data could significantly reduce dropout rates by providing targeted support. By analyzing Moodle logs, educators can determine which students are disengaged based on time spent on tasks, completion of quizzes, and contributions to forums. Predictive Learning Analytics has proven to be a valuable tool for fostering student success, particularly in large-scale online or blended learning environments where individualized attention can be complex to achieve manually.

Despite its potential, the analysis of Moodle usage reports presents some challenges. One limitation is the vast amount of data generated, which can be difficult to interpret without sophisticated analytical tools. Additionally, while time-on-task is a valuable metric, it may not fully capture the quality of student engagement. Students may spend significant time logged into Moodle without engaging with the material, leading to potential misinterpretations of their learning behaviors (Rose, 2024). Thus, combining quantitative data from usage logs with qualitative insights such as surveys or student reflections can provide a more comprehensive understanding of learner engagement. Another challenge is ensuring the privacy and ethical use of student data. With the increasing use of learning analytics, institutions must establish clear policies regarding data collection and use, ensuring that student privacy is protected while utilizing data to enhance learning outcomes (Alier et al., 2021). Moodle's open-source nature allows for customization but also places responsibility on institutions to maintain ethical standards in data-driven practices (Fink, 2022).

Analyzing Moodle usage reports offers valuable student behavior insights, enabling educators to refine their teaching strategies and improve learning outcomes. For example, by identifying common engagement patterns (or lack thereof), instructors can adjust the timing of assessments, restructure course materials, or provide additional support to less active students on the platform. Moreover, insights from data analytics can inform the development of more personalized learning experiences, as educators can tailor interventions based on individual student needs (Hakimi et al., 2024). Further research on integrating learning analytics with pedagogical practices is needed to leverage the potential of Moodle data fully. For instance, Schumacher and Ifenthaler (2021) and Cwala (2024) suggest that integrating analytics with course design can help create adaptive learning environments where content and activities are dynamically adjusted based on real-time data on student performance (Garcia et al., 2024). This approach can lead to more individualized learning paths, supporting diverse learning styles and needs. Every student entering the first course in the physics subject has a belief system and intuition about physical phenomena that originate from extensive personal experience (Lin et al., 2015).

RESEARCH METHOD

A comprehensive data-driven approach was employed to evaluate student activity and learning within Moodle, using a quantitative approach to assess learner engagement activities and learning on Moodle. This approach was designed to provide a nuanced understanding of how students interact with Moodle, the primary Learning Management System (LMS) used in the study, which was conducted in the context of this course. The methodology's primary focus was collecting, analyzing, and interpreting detailed usage reports generated by Moodle, which track various aspects of student activity, such as login frequency, time spent on tasks, content accessed, and participation in forums. The study sought to uncover student behavior patterns in their activities and learning on Moodle by analyzing these reports.

The study involved 79 undergraduate students at level 3, all of whom were formally registered for the *Information Service Support and Governance* module at Walter Sisulu University during the first semester of the 2024 academic year (January–August 2024). These students formed the target population because they were actively enrolled in the module and had consistent access to the institution's Moodle Learning Management System (LMS), from which their learning activity and engagement data were collected. The demographic composition included both male and female students aged approximately 20–24 years, representing a typical final-year undergraduate cohort in the department. These usage reports offered valuable insights into various aspects of student behavior and interaction, including how frequently students logged into the system, how much time they spent on specific learning tasks, and which course materials they accessed, ranging from lecture slides and reading materials to videos and external links. In addition, the data captured students' levels of participation in interactive components such as discussion forums and online quizzes, helping to assess their overall engagement. Assignment submission and completion rates were also tracked, shedding light on students' consistency in meeting coursework deadlines. To ensure ethical compliance and protect student confidentiality, all data were fully anonymized before analysis. This comprehensive dataset provided a solid foundation for understanding learning patterns and identifying areas where students might need additional support or intervention.

The primary research instrument in this study was Moodle's system-generated usage reports, which automatically recorded students' interactions with the online learning platform. These reports captured a wide range of behavioral data, including login frequency, time spent on specific learning tasks, access to course materials such as lecture slides, readings, videos, and external links, participation in discussion forums and online quizzes, and assignment submission and completion rates.

The assessment conducted using this instrument focused on student engagement and participation in the online learning environment. By analyzing the usage data, the study was able to evaluate how consistently and actively students interacted with course content and activities. For example, a student who logged in frequently, spent ample time on learning resources, actively participated in quizzes and forums, and submitted assignments on time was considered highly engaged, whereas a student with infrequent logins, minimal resource access, little forum activity, and late or missing assignments was identified as less engaged.

All data were fully anonymized prior to analysis to ensure ethical compliance and protect student confidentiality. Overall, the Moodle usage reports provided a comprehensive basis for understanding learning behaviors and identifying areas where students might benefit from additional support or targeted pedagogical interventions.

RESULTS AND DISCUSSION

Result

This section explores how students interacted with the Learning Management System (LMS), with a focus on their access to different parts of the course content. Figure 1 presents a chart that illustrates student engagement in the Information Technology Support and Governance course, which officially began on 15 January 2024. The chart highlights the number of students who accessed key sections of the course, such as the Welcome page, Announcements, and the Discussion forum, and those who did not. These sections are designed to provide students with essential information about the course structure, important updates from the lecturer, and opportunities for peer-to-peer interaction. By analyzing this data, we gain a clearer understanding of how students navigate the course in its early stages. For example, high access rates to the Welcome and Announcements sections may indicate that students are proactive and keen to stay informed, while low participation in the Discussion forum could suggest a need to encourage more student collaboration and communication. Overall, this analysis offers valuable insights into students' initial levels of engagement and helps identify areas where instructional strategies could be adjusted to improve participation and support learning.

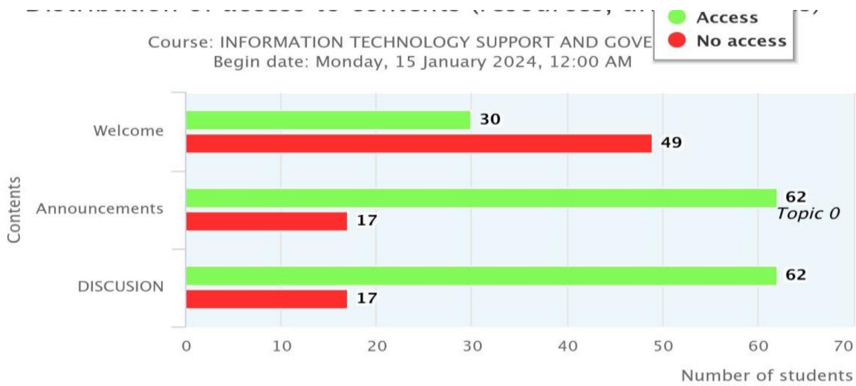

Figure 1. Distribution of student engagement with content focusing on welcome, announcements, and discussion

These sections are in Figure 1; they enhance student engagement, support timely communication, and promote a positive, collaborative learning atmosphere. Students need to access them since they give valuable information when starting a new module online. Overall engagement in the chart indicates high engagement with the "Announcements" and "Discussion" sections, both accessed by 62 students, which is about 78%, suggesting that most students engage with important course elements. However, a notable number of students (17), about 22%, consistently did not access these areas. The welcome content had the lowest engagement, with only 30 (38%) accessing it and 49 (62%) not engaging. This could indicate that students skipped or overlooked introductory information, which may be crucial for understanding course expectations. The potential issue is that 62% of students who did not access the welcome content and 22% who missed announcements and discussions may need additional outreach. Instructors could send reminders or use alternative communication methods to ensure these students know course updates and participation requirements. This analysis can help improve student engagement and ensure that no one misses essential information that could impact learning outcomes. Building on the previous analysis, a detailed investigation was conducted to examine the distribution of access to all Information Technology Support and Governance course materials, which commenced in the same period. Figure 2 categorizes the course resources by topic, highlighting the number of students who accessed or did not access each item. This breakdown provides valuable insights into student engagement patterns with various course content.

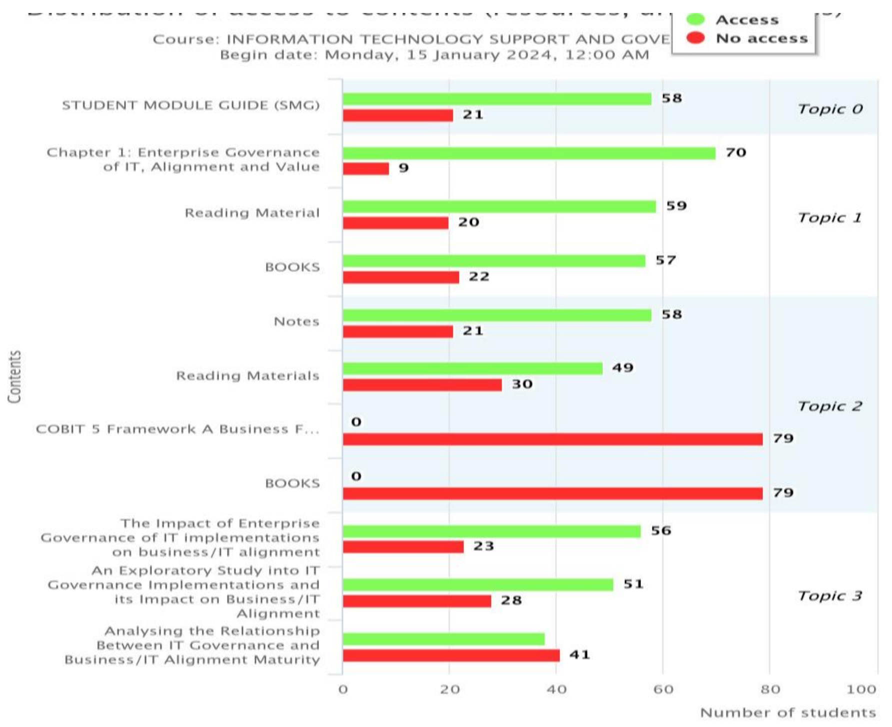

Figure. 2. Overall access to course materials

Figure 2 presents course materials grouped by topics as outlined in Moodle. The analysis reveals high student engagement in foundational areas, particularly in *Topic 0* (Student Module Guide, SMG) and the first chapter of the module. Specifically, 73% (58 students) accessed SMG, while 27% (21) did not. *Chapter 1: Enterprise Governance of IT, Alignment, and Value* showed even stronger engagement, with 89% (70 students) accessing it and only 11% (9 students) not engaging. This data highlights students' active involvement with introductory and core materials, particularly in the Enterprise Governance chapter, suggesting a keen interest in fundamental course concepts. The data in Topic 1, which includes reading materials, books, and notes for Chapter 1, reveals a strong engagement trend. Approximately 75% (59 students) accessed the reading materials, while 25% (20 students) did not, suggesting that while most students engage, a quarter may lack readiness for the course content. For books, 72% (57 students) accessed them, with 28% (22 students) opting not to. This pattern is like reading materials, indicating steady engagement. As for notes, 73% (58 students) utilized them, while 27% (21 students) did not, underscoring that students view notes as a valuable resource in their learning process. The data reveals a significant gap in *Topic 2*, as no students accessed the *COBIT 5 Framework* or the accompanying books. This absence of engagement with a key government framework raises concerns about student awareness or accessibility issues. Additionally, 62% (49 students) accessed other reading materials in this section, while 38% (30 students) did not, indicating that nearly 40% of students may be underprepared for this topic. Given its importance, the COBIT 5 Framework, a foundational IT governance resource, saw no engagement, a concerning indicator. This pattern suggests potential barriers to access, awareness, or relevance. Instructors should promptly investigate why these resources remain unused and take steps to address any accessibility or engagement challenges. *Topic 3* reveals mixed engagement levels, focusing on the critical alignment between IT governance and business strategy. While many students accessed some resources, approximately one-third to half missed key readings. Given the importance of IT and business alignment for organizational success, this engagement gap could hinder students' comprehensive understanding of the subject.

This section looks at how students interacted with the Learning Management System (LMS), focusing on which parts of the course they accessed. Figure 1 shows a chart from the Information Technology Support and Governance course, which started on 15 January 2024. The chart highlights how many students viewed important areas of the course—like the Welcome page, Announcements, and the Discussion forum-and how many didn't. These sections are important because they help students get started, stay informed, and connect with others. The Welcome page gives an overview of the course, the Announcements section shares updates from the lecturer, and the Discussion forum lets students ask questions or interact with classmates. By looking at how students use these sections, we can better understand their engagement early in the course. For example, if most students visited the Welcome and Announcements pages, it shows they were staying on top of course information. If fewer students used the discussion forum, it could mean they weren't comfortable participating yet or didn't find it necessary. This helps us see where students might need more support or encouragement to engage more fully in the course.

Figure 3 illustrates the distribution of access to *Topic 4* content in the *Information Technology Support and Governance* course, focusing specifically on assessments, with data on student access to assignments and tests.

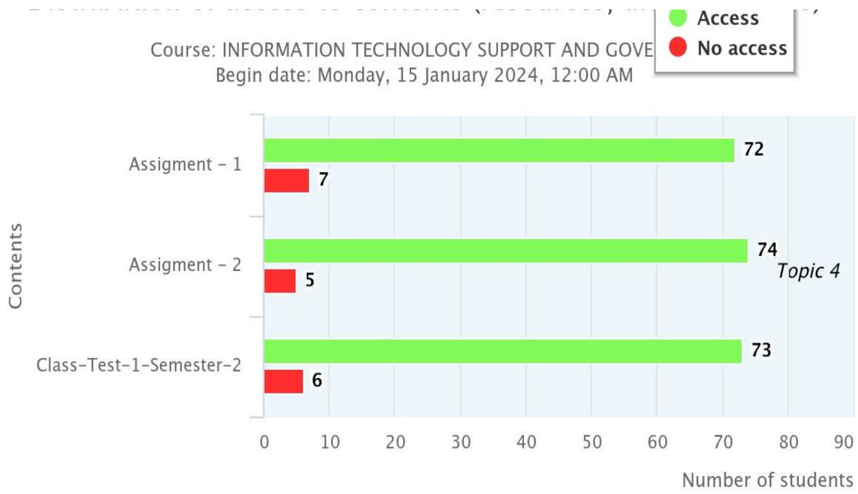

Figure 3. Distribution of access to topic 4 content

The analysis shows high engagement in Topic 4, which includes assignments and a class test, with 72 to 74 students accessing the content. This suggests that students are strongly motivated by assessments, as evidenced by the low non-access rate of only 5 to 7 students. This could be due to individual factors, such as technical issues or personal circumstances. For Assignment 1, 91%

of students (72 students) accessed the assignment, while 9% (7 students) did not. This high level of engagement reflects the importance that students place on assessments. Similarly, for Assignment 2, 94% of students (74 students) accessed the assignment, with only 6% (5 students) not accessing it. This assignment had the highest level of access, highlighting strong participation from students. In the case of the class test, 97% of students (73 students) passed the test, while only 3% (6 students) did not. Like the assignments, this high engagement indicates that students are consistently participating in assessments. Overall, student engagement with assessments in Topic 4 is exceptionally high, demonstrating a strong commitment to these key academic tasks. Building on the earlier analysis of student engagement, it became crucial to examine both student and teacher activities on Moodle from January to August 2024 to better understand the time spent on the LMS. Figure 4 provides a detailed overview of interactions within the module, revealing clear patterns of engagement from both students and teachers.

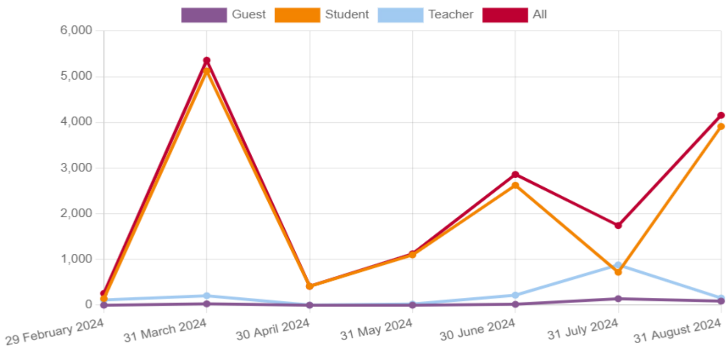

Figure 4. Student and teacher activities on Moodle

The graph visualizes activity over time for different user types—Guest, Student, Teacher, and All-between February 29, 2024, and August 31, 2024. Monthly activity levels for each user type are plotted to show engagement trends over time. This study specifically focuses on student and teacher activities, with key insights highlighted by color:*Student activity* is represented by the orange line, and *the blue line represents teacher activity*. The peak in student activity, highlighted in orange, occurred around March 31, 2024, with activities surpassing 5,000. This surge likely corresponds to the start of an academic term or a significant assignment deadline, reflecting heightened student engagement. Following this March peak, activity dropped significantly in April and May, reaching a low point in June, possibly due to breaks, holidays, or reduced academic demands. Engagement levels picked up again in July and rose further in August. However, they did not reach March's peak, likely indicating the start of a new active academic period or preparations for the upcoming semester. In contrast, shown in blue, teacher activities remained relatively low and consistent throughout the months, with a slight peak in July. This pattern suggests that teachers primarily engage at specific times, likely for course preparation, uploading materials, or during student assessment periods. This tells us that the teacher's primary role was to upload content and other materials related to the module. The significant spike in March reflects high student involvement, likely fuelled by academic deadlines or exams. However, engagement experienced a substantial decline through mid-year, indicating reduced academic activity or holidays. Both student engagement and overall activity experienced a resurgence in August, signalling the commencement of new academic cycles or upcoming assignments. Teacher activity remained stable throughout this period, suggesting a consistent workload associated with specific academic events such as grading or planning sessions. Figure 4 shows the trend between teacher views and posts.

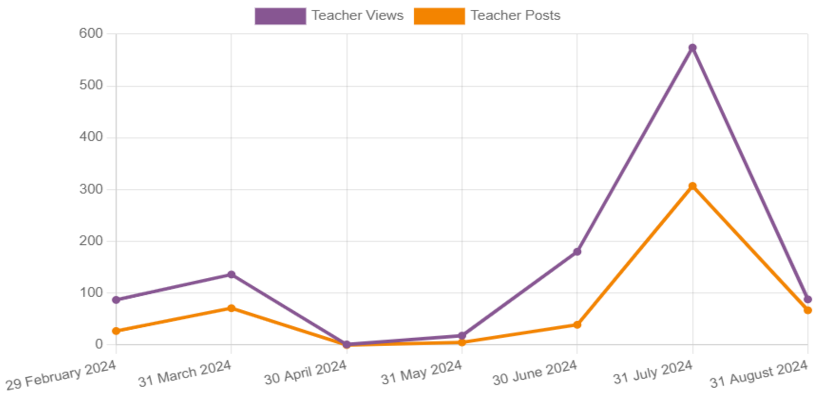

Figure 5. Teacher views and posts

The graph in Figure 5 illustrates the trends in Teacher Views (purple line) and Teacher Posts (orange line) over time, spanning from February 29, 2024, to August 31, 2024. It provides insight into how teachers interacted with the platform regarding viewing and posting content.

Teacher Views (Purple Line)
Teacher views started at a moderate level of around 100 at the beginning of March 2024, which slightly increased by the end of the month. There was a sharp drop in teacher views from April to May, reaching almost zero in June. This could be attributed to the end of an academic term or break periods, leading to decreased engagement. Teacher views surged dramatically in July, peaking at around 600 views. This could signal preparation for a new academic session, where teachers may have reviewed or updated course content. After the July peak, there was a sharp decline in August, though teacher views remained higher than in earlier months.

Teacher Posts (Orange Line)
Teacher posts remained relatively low, hovering between 50 and 100 posts from February to April 2024. Posting activity dropped to almost zero between May and June, indicating a lull in contributions, possibly due to academic breaks or fewer class activities. Posting activity increased again in July and August, coinciding with the spike in views. However, even in August, posts did not rise as dramatically as views, suggesting that the teacher actively contributed new material while teachers were reviewing content. There is a noticeable difference between the number of teacher views and posts. The teacher was far more likely to review content than to create or contribute posts. This is especially evident in July, where views peaked, but posts only increased moderately. The low teacher activity in views and posts from April to June reflects a period of minimal engagement, likely corresponding to academic holidays or non-teaching periods. However, engagement surged in July, likely tied to the start of a new term or preparation for upcoming academic activities. The peak in teacher views suggests that teachers are actively reviewing resources, potentially preparing for the start of the academic year in July and August. However, the relatively low number of posts, even during peak months, may indicate that more passive engagement (reviewing content) is every day while fewer teachers actively create new content or participate in discussions. This analysis can guide strategies to boost teacher involvement and optimize the balance between passive and active engagement throughout the academic year. After analyzing teacher views and posts, it was equally intriguing to explore student perspectives and contributions and examine the trends and consistency in their participation. Figure 6 illustrates student views and posts.

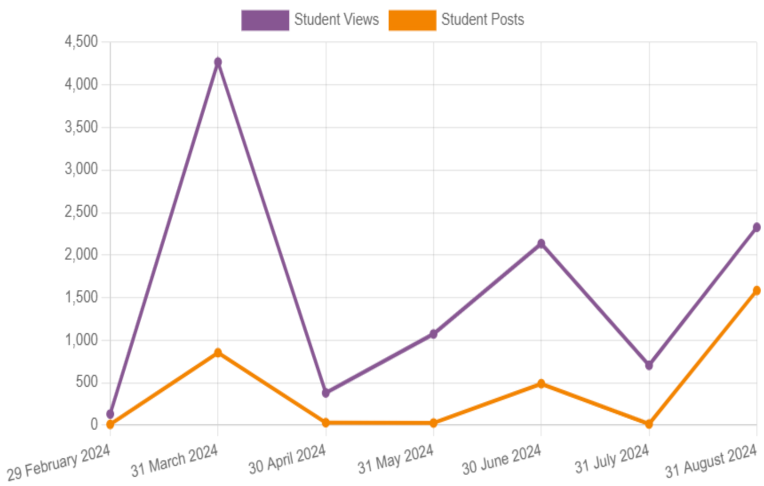

Figure 6. Student views and posts.

The graph compares Student Views (purple line) and Student Posts (orange line) between February 29, 2024, and August 31, 2024. The data shows the students' interactions with the platform, broken down into how frequently they viewed course materials versus how often they actively posted content.

Student Views (Purple Line)
There was a significant increase in student views, peaking at nearly 4,500 in late March 2024. This spike suggests a significant engagement likely driven by upcoming assignments, exams, or project deadlines. Significant Decline from April to June:After March, views dropped sharply, dipping below 1,000 views by June. This drop indicates a potential break-in in academic activities or a period of less intensive study. Rising Trend in July and August:Student views rose again in July, reaching nearly 3,000. This increase suggests that students were preparing for a new academic term or returning to more intensive study sessions.

Student Posts (Orange Line)
The number of student posts remained significantly lower than views throughout the entire period, with the highest post count being around 500 in August. This is because the students mostly viewed and accessed the material rather than posted as the teacher. There was a modest increase in posting activity, especially in July and August, reflecting rising engagement in discussions or assignment submissions, though posts remained far lower than views.

Student views are highest in March and August, suggesting these periods correspond to key academic deadlines (like exams or significant assignments). The sharp decline in views between April and June likely corresponds to breaks in the academic calendar. Student engagement in terms of posting content remains consistently low compared to views. Even when students actively viewed content in large numbers (March), relatively few contributed posts. This could indicate a preference for passive engagement (reviewing materials) rather than actively participating in discussions or posting content. Both views and posts showed an upward trend during July and August, indicating increased student activity as the new academic session begins or as the semester progresses.

CONCLUSION
In conclusion, this study provides valuable insights into student engagement patterns and learning behaviors within the Moodle LMS. By analyzing usage data across various topics, assignments, and assessments, we identified clear peaks in activity around academic deadlines and assessments, underscoring the motivational impact of these events on student participation. However, low engagement with supplementary resources and a general lack of continuous

interaction reveal potential areas for improvement in sustaining engagement throughout the semester. The findings suggest that fostering a more interactive and collaborative learning environment on Moodle could help bridge these engagement gaps. Strategies such as incorporating regular discussion prompts, offering timely feedback, and encouraging peer-to-peer interactions may promote ongoing involvement. This continuous engagement can improve content comprehension and enhance overall learning outcomes by creating a more dynamic and supportive online learning experience. Ultimately, this study highlights the importance of data-driven insights for educators to optimize online learning environments, tailoring support to meet student needs better and foster more profound engagement with course content.

As indicated by views, student engagement tends to peak around significant academic events, such as assignment deadlines and exams. However, the posting activity remains relatively low, suggesting limited interaction beyond content review. Encouraging more consistent and active participation throughout the semester could enhance engagement. This paper recommends that since engagement with announcements is low, finding alternative communication methods to alert students about important resources could be beneficial in enhancing communication. Teachers need to continuously identify students who have not accessed key resources and reach out to provide support or reminders as a form of intervention for non-engaged students.

Teachers must consider integrating participation or quizzes based on reading materials to motivate students to actively engage with the content and encourage resource engagement. With a substantial difference between views and posts, strategies to encourage more active engagement (e.g., interactive assignments and discussion prompts) would be beneficial to increase student contributions and encourage active participation. Given the high number of views but lower posting activity, it may be beneficial to encourage more active contributions from teachers, such as creating discussions or sharing resources.

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