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Exploring students' learning experience toward the learning management system and the impact on their academic performance

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Abstract

Learning Management Systems (LMS) are widely used in higher education to enhance learning access and flexibility. However, the link between LMS engagement, such as time spent online and the use of learning analytics and academic performance remains unclear. This study investigates the relationship between students' LMS usage patterns (time spent, independent learning behavior, learning analytics utilization, and GPA) and their academic performance in a Basic Electronics course at a major university in Aceh, Indonesia. Data were collected using a validated questionnaire with 45 items (Cronbach's alpha = 0.92). The analysis reveals that independent learning behavior and GPA are significantly associated with students' academic performance. In contrast, time spent on the LMS and the use of learning analytics tools show a weaker or insignificant relationship with assessment outcomes. These findings suggest that promoting learner autonomy and maintaining consistent academic achievement are more critical for success than simply increasing LMS usage. Educators should therefore focus on fostering independent study skills and academic discipline, rather than relying solely on technological engagement metrics.

Keywords: Academic performance, Higher education, Independent learning behavior, Learning analytics, Learning Management System (LMS).

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1. Introduction

Learning analytics encompasses measuring, collecting, analyzing, and reporting data related to learners and their environments [1]. Its primary objective is to understand and improve both learning and the contexts in which it occurs [2]. This broad definition, first articulated in 2011 for the inaugural Learning Analytics and Knowledge (LAK) conference, remains relevant despite the field's evolution. Over the past decade, learning analytics has expanded significantly as both an academic discipline and a commercial industry [3, 4]. It intersects with various fields, including educational research, learning sciences, assessment, educational technology, statistics, data visualization, computer science, artificial intelligence, usability, participatory design, and sociotechnical systems thinking [5-7].

Learning Management Systems (LMS) adoption in education has increased significantly in recent years, driven by the growing demand for flexible and personalized learning experiences. These platforms serve as centralized hubs for instructors to manage and deliver course content, monitor student progress, and provide feedback [8, 9]. However, it is crucial to move beyond the basic functionalities of LMS and incorporate advanced analytics tools to further enhance the learning experience for students. Learning analytics is of significant importance in education, offering numerous benefits for both learners and educators. One crucial aspect is its role in enabling personalized learning experiences. By utilizing data from various sources, such as learning behaviors and performance, learning analytics provides educators with insights into individual learner preferences, strengths, and weaknesses [10, 11]. This information empowers educators to tailor learning content, approaches, and resources to meet the specific needs of each learner, fostering a more effective and engaging learning process.

Furthermore, learning analytics facilitates real-time feedback mechanisms. Learners and educators can access immediate insights into progress, performance, and learning strategies [12]. This timely feedback not only helps learners monitor their advancement but also assists educators in adapting their teaching methods to suit individual or group requirements [13]. Consequently, learners remain motivated and engaged, while educators can promptly address any impediments to effective learning. The integration of learning analytics also promotes data-driven decision-making in education. Educators can leverage the wealth of data to make informed choices about curriculum design, instructional approaches, and assessment methods. By basing their decisions on empirical evidence, educators ensure that their teaching practices are grounded in efficacy and innovation, resulting in improved learning outcomes [14, 15].

Another critical aspect of learning analytics is its role in driving continuous improvement. Educators can use analytics to identify areas where teaching strategies can be enhanced and interventions optimized [15, 16]. Through ongoing analysis of data, educators gain insights into the effectiveness of their teaching methods and can implement evidence-based adjustments, leading to more successful learning experiences. Beyond the classroom, learning analytics contributes to institutional effectiveness. Educational institutions can assess the impact of their programs and interventions by analyzing data on student performance and engagement [17]. This information aids in identifying areas that require attention or modification. With such insights, institutions can allocate resources more judiciously, design more effective programs, and develop informed policies to enhance overall educational quality [18].

Data from an LMS to assess students' learning behaviors can be used to take several actionable steps to enhance educational outcomes. Educators can personalize learning pathways by tailoring plans to individual needs, providing targeted interventions for struggling students, and refining instructional strategies based on effective methods [19]. Real-time feedback can be offered to help students track their progress, while engagement can be improved through interactive and gamified elements. Course content can be optimized by focusing on frequently accessed materials, and collaborative learning can be encouraged to enhance peer interactions [20]. Data-driven decision-making supports curriculum and assessment improvements, while predictive analytics can help prevent dropouts by identifying at-risk students. Additionally, institutions can use aggregated data to refine policies and programs, and educators can receive professional development to better utilize analytics, fostering a more responsive and student-centered learning environment. Therefore, this study is crucial to conduct in order to improve the LMS for a better student learning experience.

2. Literature Review

2.1. History of Online Learning Management Systems in Education

The concept of online Learning Management Systems (LMS) in education can be traced back to the late 20th century, emerging alongside advancements in computer technology and the internet [21, 22]. The earliest form of online education began in the 1960s with the creation of computer-based training (CBT) programs. However, it wasn't until the 1990s, with the proliferation of personal computers and the internet, that LMS platforms started to take shape and become more sophisticated [23, 24]. One of the earliest and most notable LMS platforms was PLATO (Programmed Logic for Automated Teaching Operations), developed in 1960 at the University of Illinois. PLATO was a computer-based education system that utilized mainframe computers to deliver educational content and assessments. Although initially not an online system, it laid the groundwork for future developments in educational technology.

In the 1990s, as the internet became more accessible, several key LMS platforms were introduced. Blackboard, founded in 1997, became one of the first widely adopted online LMS platforms. It offered a range of tools for course management, content delivery, and student assessment, quickly becoming popular in higher education institutions. Around the same time, WebCT (Web Course Tools) was developed by a faculty member at the University of British Columbia. Launched in 1996, WebCT provided a web-based platform for creating and managing online courses, eventually merging with Blackboard in 2006.

The early 2000s proverb significant growth and diversification in the LMS market. Moodle, an open-source LMS, was introduced in 2002 by Martin Dougiamas. Its flexibility, community-driven development, and cost-effectiveness made it a popular choice among educational institutions worldwide. Similarly, Desire2Learn (now known as Brightspace) was launched in 1999, offering a cloud-based LMS solution with a focus on learning analytics and personalized learning. These platforms evolved rapidly, incorporating new features such as mobile compatibility, social learning tools, and advanced analytics. The shift towards cloud-based solutions in the late 2000s further enhanced the scalability and accessibility of LMS platforms, allowing institutions to manage and deliver education more efficiently.

2.2. Modern LMS and Future Directions

Today, LMS platforms have become integral to educational institutions at all levels, supporting diverse learning environments from K-12 to higher education and corporate training. Modern LMS platforms, such as Canvas (launched in 2011), offer comprehensive features including mobile access, integration with third-party applications, and robust analytics capabilities. The ongoing development of artificial intelligence and machine learning continues to drive innovation in LMS, enabling more personalized and adaptive learning experiences [25]. The future of LMS is poised to be shaped by advancements in technology and pedagogy, with an increasing focus on student engagement, data-driven insights, and seamless integration with emerging educational tools. As online education continues to expand, LMS platforms will play a crucial role in facilitating effective and accessible learning experiences across the globe [26].

A learning management system (LMS) must have several key features to be effective. These include user-friendly course creation tools that allow educators to design and organize content, a robust system for tracking and assessing student progress, and support for various multimedia formats [27]. It should facilitate communication and collaboration through forums, chats, and messaging. Additionally, the LMS should integrate seamlessly with other educational technologies and platforms, provide secure and scalable access, and offer customizable reporting and analytics to monitor and improve learning outcomes. Finally, mobile accessibility and compliance with educational standards and regulations are essential for a comprehensive LMS [28, 29]. Some common features that LMS could be inherently integrated into the platform are depicted in Figure 1.

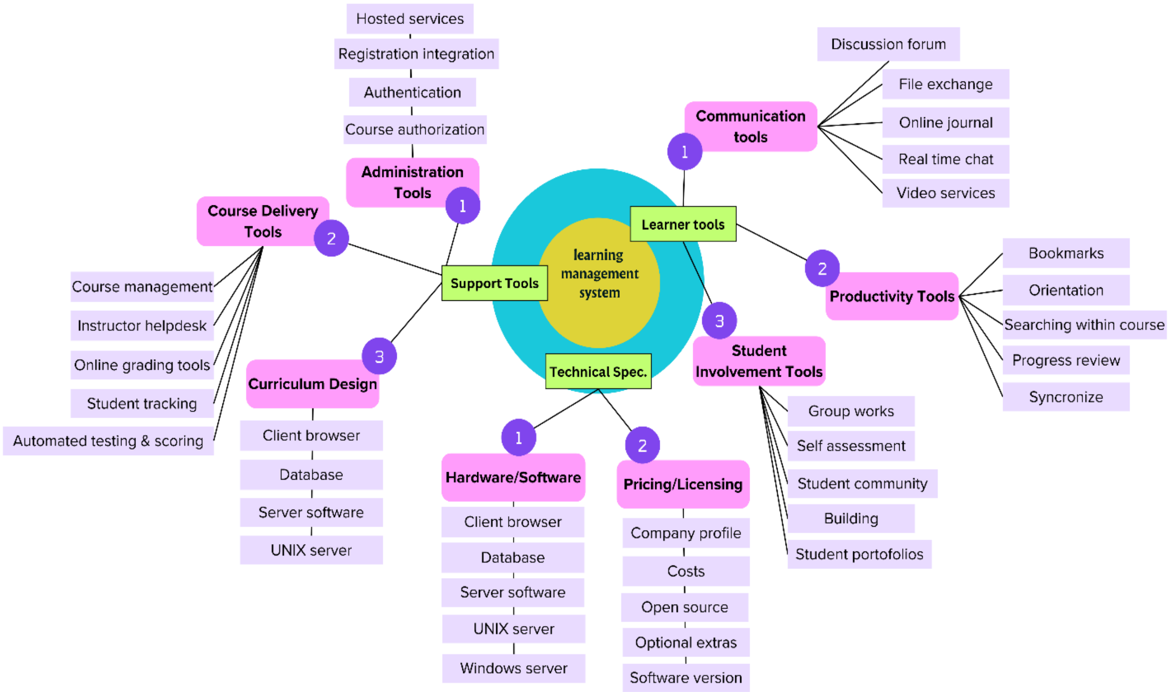

Figure 1.
Typical features (components) of LMS.

The diagram suggests a detailed visualization of a Learning Management System (LMS), demonstrating the layered complexity that underpins modern online education. At the center of this system are the learner tools, which are crucial for enhancing the educational experience [30]. These tools include various communication mechanisms, such as discussion forums, real-time chat, and video services, which foster interaction between students and instructors, thereby creating a collaborative learning environment. Additionally, productivity tools like bookmarks, course orientation aids, and progress review features are integral in helping students navigate and manage their coursework efficiently, ensuring they stay on track and engaged with the material [31]. The learner tools are support tools that play an essential role in maintaining the operational integrity of the LMS. Administration tools form the backbone of these support mechanisms, handling essential processes such as registration integration, authentication, and course authorization [32]. These ensure that the system operates seamlessly, providing a secure and structured platform for both students and instructors. Course delivery tools are equally important, encompassing everything from course management systems to automated testing and scoring mechanisms. These tools not only facilitate the dissemination of educational content but also provide the necessary infrastructure for tracking student progress and managing instructor-student interactions [33, 34].

Another critical component of the LMS is curriculum design, which is closely tied to the technical specifications of the system. This involves the integration of client browsers, databases, server software, and UNIX servers, all of which are necessary for the effective development and maintenance of educational content. The diagram also highlights the hardware and software requirements, emphasizing the importance of a robust technological foundation that supports the entire system. This includes both client-side and server-side components, ensuring that the LMS is scalable, reliable, and capable of handling the demands of a diverse user base [28, 35-38].

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2.3. Learning Analytics Feature and its Integration to LMS

The integration of learning analytics features in LMS began to form in the early 2000s, but it gained significant traction around the mid-2000s. The development of these features was driven by the growing recognition of the potential to enhance teaching and learning through data-driven insights. The concept of learning analytics emerged as educational institutions sought more effective ways to monitor and improve student learning outcomes. Early LMS platforms, such as Blackboard and WebCT, started incorporating basic analytics tools in the mid-2000s. These tools primarily focused on tracking student activity, such as login frequency, time spent on various course components, and participation in discussion forums.

The significant advancements in learning analytics began in the early 2000s, coinciding with the increasing adoption of LMS in educational institutions. For example, Desire2Learn (now Brightspace) introduced more sophisticated analytics features that went beyond simple activity tracking. These included tools for assessing student performance, identifying at-risk students, and providing personalized feedback based on data analysis. By the early 2010s, learning analytics had become a more integral component of LMS platforms. The introduction of open-source LMS like Moodle facilitated the development and integration of advanced analytics plugins and modules. Additionally, proprietary LMS platforms such as Canvas (launched in 2011) incorporated robust learning analytics features from the outset, emphasizing the use of data to enhance educational outcomes.

Currently, modern LMS platforms offer comprehensive learning analytics capabilities, including:

1. Real-Time Data Visualization: Dashboards and visual reports that provide real-time insights into student engagement and performance.
2. Predictive Analytics: Algorithms that identify patterns and predict future student performance, helping educators intervene proactively.
3. Personalized Learning Paths: Customization of learning experiences based on individual student data, enabling tailored instruction and resources.
4. Interactive Data Reports: tools that allow educators to drill down into specific data points to better understand student behavior and outcomes.

The integration of learning analytics in LMS has significantly impacted education by enabling data-driven decision-making [39-44]. Educators can now use analytics to refine their teaching strategies, provide timely interventions, and enhance overall student learning experiences. As technology continues to evolve, future advancements in artificial intelligence and machine learning are expected to further enhance the capabilities of learning analytics, making LMS even more powerful tools for education.

2.4. Research on Learning Analytics

Research on learning analytics has demonstrated significant impacts on educational improvement, as evidenced by several studies published in reputable international journals. Viberg et al. [45] conducted a systematic review in Computers & Education, highlighting the positive influence of learning analytics on student outcomes in higher education, particularly in enhancing academic performance and retention rates. Similarly, Sclater et al. [46] reviewed the implementation and outcomes of learning analytics practices in the UK and internationally and found that these practices effectively improved student engagement and success.

The study conducted by Zhang and Liu [43] explored the predictive power of learning analytics in identifying at-risk students in online graduate programs, demonstrating its potential to support early interventions and improve retention. Another study by Gašević et al. [47] investigated how personalized learning environments created through analytics positively impacted student engagement and academic success. Ifenthaler and Yau [48] provided a systematic review of the literature on learning analytics' influence on student success, highlighting key findings and future research areas.

Additionally, Maren et al. [44] reviewed various learning analytics intervention models, demonstrating their efficacy in supporting data-driven decision-making in educational settings. While Tsai and Gasevic [49] examined the effects of learning analytics on both learning and teaching environments, identifying significant benefits and challenges. These studies collectively illustrate the transformative potential of learning analytics in enhancing educational outcomes and supporting effective teaching practices.

3. Materials and Methods

This research explores the behavior of students in utilizing the features of the Learning Management System (LMS) and learning analytics on the Moodle platform on the USK e-learning website. The study focuses on three main aspects: 1) the duration and relevance of LMS usage, 2) students' learning autonomy in the context of LMS usage, and 3) students' self-efficacy in using learning analytics features to support higher education learning success.

This research employs a mixed-method approach, integrating both qualitative and quantitative methods. Data related to the experiences of using the LMS, learning autonomy, and understanding of learning analytics are analyzed and discussed using a qualitative approach. Meanwhile, the quantitative approach is utilized to measure the impact of self-efficacy in using learning analytics features within the LMS on students' academic performance.

Overall, student performance on the final examination score was set as the dependent variable in this study since the main purpose was to examine the relationship between academic performance and several factors labeled as independent variables. The independent variables were obtained from a questionnaire comprising 45 questions covering three criteria: LMS usage (10 items), learning autonomy (10 items), and learning analytics (25 items). Details of each criterion and its respective sub-criteria can be found in Table 1. The variables used in this study are described as follows:

- Dependent variables:
  (i) MarkFinalExam (Y)
- Independent variables:
  (i) Total time in minutes spent on the LMS
  (ii) Independent learning score
  (iii) Learning analytics efficacy of students
  (iv) GPA

Table 1.
Criteria and sub-criteria of the questionnaire and the reliability scale (alpha).

No	Criteria	Sub-criteria	No of item	Cronbach's alpha
1	Learning management system usage	Duration of use	2	0.66
		Course content access	2	
		Quiz access	2	
		Quiz quality	2	
		Course announcement access	2	
2	Learning independence	Duration of LMS used for independent learning	2	0.64
		Course content access during independent learning	2	
		Independence in quiz attempt	2	
		Independence in doing assignments	4	
3	Learning analytics	Level of understanding of the learning analytics feature	2	0.93
		Learning analytics usage frequency	2	
		The role of learning analytics in course completion	4	
		The use of LA in learning strategy	2	
		Impact of LA on students' motivation	2	
		Impact of LA on students' learning outcomes	3	
		Overall experience of LA	5	
		Preference and recommendation	5	
Total			45	0.92

Table 2.
Respondent Demography.

Demographic variables	Frequency (N=129)	Percentage (%)
Age (Yrs)		
18-19	40	31
20-21	51	39.5
22-23	38	29.5
Gender		
Male	13	10.1
Female	116	89.9
Semester		
2	23	17.8
4	34	26.3
6	32	24.8
8	37	28.7
10	3	2.3
GPA (Scale of 4)		
>3.5	59	45.7
3-3.5	67	51.9
<3	3	2.3

3.1. Statistical Analysis

The quantitative analysis of OLS was performed using SPSS version 25 at a significance level of 0.05.

4. Results

Prior to regression analysis, we conducted an exploratory descriptive analysis of the data. The distribution plots of all variables were examined for evidence of atypical values. Using statistical methods (median, interquartile range multiples, etc.), we determined the workable sample of 129 students. The distribution plots of the variables were all acceptable, with the dependent variable exhibiting approximately normal behavior. All dependent variable data, both learning independence learning and learning analytics data, were displayed as percentages; time spent was expressed in minutes, and the GPA as a numerical scale of 0-4. The descriptive data is depicted in Table 3.

Table 3.
Descriptive summary statistics.

Vars	Mark Final Exam	Time Spent	Learning Independence	Learning Analytics	GPA
N	129	129	129	129	129
Mean	84.86	420.00	70.09	74.68	3.45
Median	85.00	240.00	70.00	75.00	3.48
SD	4.77	220.96	7.79	9.84	0.23
Minimum	78.00	240.00	50.00	41.00	2.64
Maximum	95.00	900.00	85.00	100.00	4.00

Correlation analysis of the variables was also conducted to assess the strength of association of the independent variables with the two dependent variables (MarkFinalExam and MarkOther). The variables learning independence and GPA had reasonably strong correlations with the dependent variables ($p<0.05$). While the independent variables Time Spent and Learning Analytics exhibited reasonable strength of association reflect the absence of collinearity problems for estimation.

4.1. Student Behavior in Utilizing LMS for Learning Activities

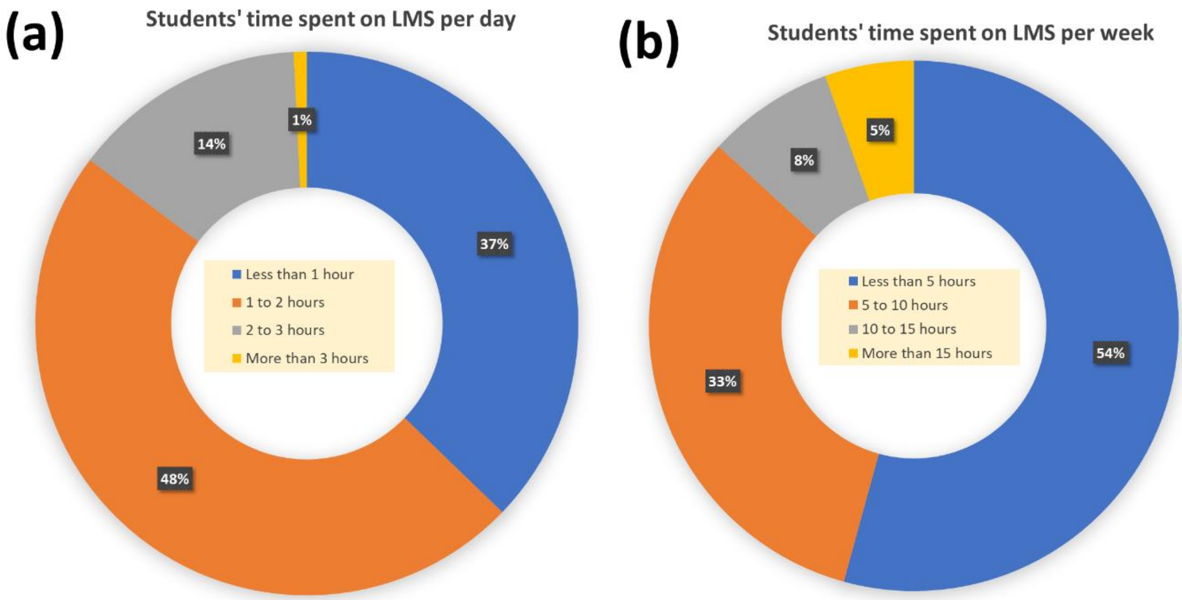

Figure 2.
Students' average time spent on the LMS (a) per day and (b) per week.

Figure 2 shows that the average student spends only 1 to 2 hours per day, and more than half of them spend less than 5 hours per week accessing the LMS during their courses. Only a small portion, around 5%, of students access the LMS for 15 hours per week. This data reflects a lack of student interaction with the LMS. Student interaction with the LMS is an indicator of student engagement with an online learning system, which is one of the critical factors for the success of e-learning. Several researchers have stated that the duration of students' use of the LMS is closely correlated with their academic performance Korkofingas and Macri [50] reported that the amount of time spent by students at a business campus of a major university in Australia on the LMS had a positive correlation with their academic performance..

However, in this study, we found that the duration of time students spent on the LMS did not have a significant impact on their academic performance. The amount of time a student spends on a Learning Management System (LMS) does not necessarily correlate with their academic performance for several key reasons. First and foremost, the quality of engagement with the material is far more important than the quantity of time spent online. Students who engage deeply with course materials, participate in discussions, and critically think about what they're learning tend to perform better, regardless of whether they spend extensive hours logged into the LMS. Time spent passively browsing or skimming through content does not translate into meaningful learning, as academic success is built on comprehension and critical engagement, not just exposure to information. Additionally, different students have varying learning styles and levels of efficiency; some comprehend concepts quickly and need less time on the LMS, while others may need more time to achieve the same level of understanding. Moreover, academic performance is influenced by a wide range of factors beyond the LMS, such as a student's motivation, study habits, and prior knowledge. A student who may be highly motivated and organized could outperform others with minimal time spent on the LMS, while another student may struggle despite a significant online presence due to personal challenges or a lack of foundational understanding. In addition, it is also important to recognize that students often use multiple sources for learning, such as textbooks, peer discussions, or external websites that are not reflected in LMS time logs, yet still contribute significantly to their academic progress.

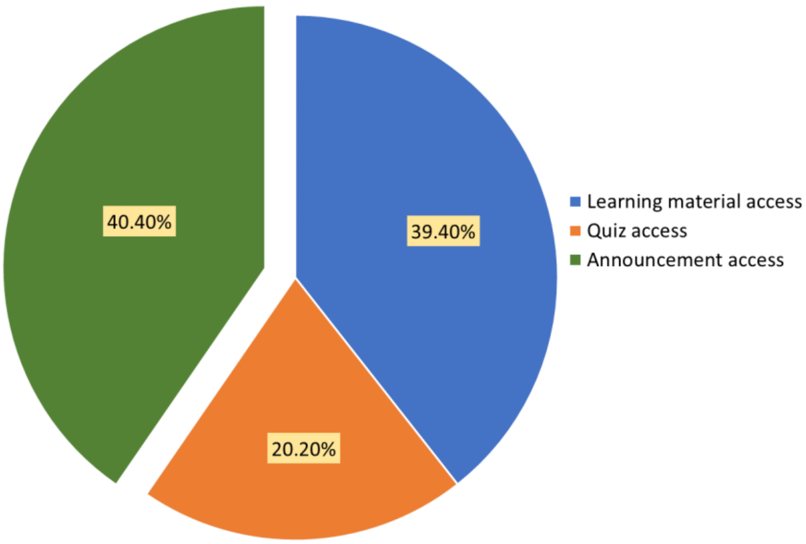

Figure 3.
The purpose of LMS access by students during e-learning process.

When further explored with students about the purpose of accessing LMS as shown in Figure 3, it is remarkable that a significant amount of time (40.4%) is spent on accessing announcements, nearly as much as on learning materials (39.4%). This raises an important consideration when discussing the relationship between time spent on the LMS and academic performance.

One potential reason why time spent on announcements might not correlate significantly with academic performance is that announcements typically provide logistical or organizational information, such as deadlines, changes in schedules, or event reminders. While important for managing coursework, they do not directly contribute to a student's understanding of the course content or skills development, which are more closely linked to performance on assessments. Therefore, although students might spend a lot of time checking announcements, this activity does not require deep cognitive engagement or lead to improved comprehension of course materials. In contrast, learning material access (39.4%) and quiz access (20.2%) are more likely to contribute directly to student learning outcomes, as they involve interaction with educational content and self-assessment, both of which are essential for knowledge acquisition and retention. Time spent on these activities reflects actual learning engagement and can more directly impact performance on assignments, quizzes, and exams.

Further analysis using OLS regression suggests that the factors of learning independence and GPA of students are positively correlated with the final exam scores of students in the online classroom of the Basics Electronics course. The statistical output details are depicted in Table 4.

Table 4.
The regression result-Dependent Variable (Y) (MarkFinalExam%).

Variables	Unstandardized Coefficients	Std. Error	Standardized Coefficients	t-values	p-values
(Constant)	27.863	4.153		6.709	0.000
TimeSpent	0.002	0.001	0.080	1.389	0.167
LearningIndependence	0.032	0.100	0.021	0.318	0.007
LearningAnalytics	-0.005	0.030	-0.010	-0.170	0.865
GPA	16.131	1.149	0.796	14.040	0.000
R	R-Square	Adj. R-Square	Std. Error	F	Sig.
0.800	0.640	0.628	2.910	55.060	0.000

The results of the regression analysis reveal important insights into the relationship between the independent variables (Time Spent, Learning Independence, Learning Analytics, and GPA) and the dependent variable (Final Exam Mark). Particularly, GPA stands out as the most influential predictor, with a large positive unstandardized coefficient (16.131) and a high standardized coefficient (0.796). This suggests that GPA has a strong and statistically significant impact on the dependent variable, contributing more to the model's explanation of variance than any other predictor. The p-value for GPA (0.000) confirms its significance, and the high t-value (14.040) reinforces its role as a key driver in the model. The strong correlation between GPA and the dependent variable suggests that academic performance, as reflected in GPA, plays a crucial role in shaping the learning outcome, perhaps serving as an indicator of overall academic or personal success in contexts where the final exam score could reflect measures like achievement or performance in the online learning classroom.

5. Discussion

On the other hand, Learning Independence, while statistically significant with a p-value of 0.007, has a much smaller effect on the dependent variable. The unstandardized coefficient (0.032) and standardized coefficient (0.021) indicate that although Learning Independence contributes to the model, its influence is relatively minor compared to GPA. Time Spent and Learning Analytics, with p-values of 0.167 and 0.865, respectively, do not make significant contributions to the final exam marks. This suggests that the amount of time spent and the use of learning analytics tools do not meaningfully impact the outcome in this particular model, since the time used by students on the LMS is mostly for announcements. The overall model fit is strong, as evidenced by an R-squared value of 0.640, meaning 64% of the variance in the dependent variable is explained by the predictors. The adjusted R-squared (0.628) is also robust, indicating a good balance between the model's complexity and its explanatory power. Finally, the significant F-value (55.060, p-value 0.000) confirms that the model, as a whole, is statistically significant and meaningful in predicting the dependent variable.

Independent learning ability plays a crucial role in enhancing academic performance, whether in an online learning setting or a face-to-face learning environment [51]. Students who develop strong independent learning skills can manage their own learning processes more effectively, setting goals, self-assessing their progress, and employing time management strategies. This self-directed approach enables them to actively engage with the material, seek out additional resources, and take responsibility for their academic growth. By fostering autonomy, students become less reliant on external direction, enabling them to deepen their understanding and retain information more effectively [52].

In an online learning setting, where students often have greater flexibility and fewer direct interactions with instructors, independence becomes even more important. Independent learners thrive in this environment because they are better equipped to manage the open structure of online education [53, 54]. They can plan their study time, access course materials on their own, and actively engage with online resources without needing constant guidance. Furthermore, independent learners are more likely to take advantage of opportunities like discussion boards, digital libraries, and self-assessment tools, helping them stay on track and achieve higher academic outcomes. Their ability to organize and self-motivate is essential for success in the less structured and more autonomous online learning environment [55-57].

In face-to-face learning, independent learners benefit from their ability to take initiative in the classroom. While traditional settings provide more direct interaction with instructors, independent students do not simply rely on lectures or classroom activities. Instead, they engage actively by asking questions, participating in discussions, and seeking out additional learning opportunities, such as extracurricular activities or academic research [58-60]. Outside the classroom, their independence allows them to reinforce and extend what they have learned, whether through self-study, collaborative projects, or exploring new topics. This proactive approach ensures they not only absorb the material taught but also develop a deeper understanding that enhances their overall academic performance. Independent learners are thus better prepared to succeed, regardless of the mode of learning [61, 62].

5.1. Implications of the Study and Further Suggestions

The regression analysis provides key insights into how different factors influence final exam performance (Mark Final Exam). The findings suggest that time spent studying alone does not significantly affect exam results. This implies that students might need to focus more on effective study techniques rather than simply increasing study hours. On the other hand, learning independence plays a small but statistically significant role, indicating that students who are more self-directed in their learning tend to perform better on exams. This underscores the importance of promoting self-regulated learning strategies, such as time management, self-assessment, and critical thinking, in education. Surprisingly, the use of learning analytics tools shows no significant impact on exam performance. This may suggest that students are either not utilizing these tools effectively or that the tools themselves do not provide direct benefits for improving exam scores. This raises questions about how such tools are integrated into learning processes and whether they need to be better aligned with students' needs to be effective.

To improve the quality of online learning and support increased student academic performance, a few key changes can be made based on the findings from the regression analysis. First, fostering learning independence is critical. Since independent learners tend to perform better on exams, online courses should focus on promoting self-regulation skills. This could be achieved through structured learning paths, self-assessment tools, and resources like workshops on time management and goal-setting. Encouraging collaboration through group projects and peer-to-peer learning can also foster independence while promoting accountability.

Additionally, the results suggest that time spent studying does not necessarily equate to better performance. To address this, the focus should shift from the amount of time spent studying to the quality of study time. Providing students with effective learning strategies, such as metacognitive approaches and active learning techniques, can help them make the most of their study efforts. Personalized feedback and engaging, interactive resources will also enhance the effectiveness of study time.

Finally, the use of learning analytics tools should be optimized. The current lack of impact suggests that either students aren't using these tools effectively, or they don't understand how to leverage the data for improvement. Offering training on how to interpret learning analytics and presenting data in a way that provides actionable insights can make these tools more valuable. Additionally, integrating adaptive learning platforms and real-time feedback systems can further personalize the learning experience and support student success. These adjustments will ensure that online learning environments are more supportive of student growth and academic performance.

6. Conclusion

In conclusion, while factors like learning independence contribute positively to final exam performance, merely spending more time studying or using learning analytics tools does not guarantee improved outcomes. The strong influence of GPA on exam scores suggests that overall academic performance remains a crucial indicator of success. To enhance final exam performance, educators should focus on encouraging stdents to develop independent learning skills and adopt more effective study habits, rather than relying on study duration or technology alone. These results also call for a reassessment of how learning analytics tools are implemented in educational settings, ensuring they are used in ways that genuinely support student learning.

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