Cite this chapter

Ferreira, R., Cardoso, E., Oliveira, J. (2023). How Can LMS Affect Student's Motivation and Engagement?. In: Pereira, R., Bianchi, I., Rocha, Á. (eds) Digital Technologies and Transformation in Business, Industry and Organizations. Studies in Systems, Decision and Control, vol 497. Springer, Cham. https://doi.org/10.1007/978-3-031-40710-9_10

How can LMS affect student's motivation and engagement

Rui Ferreira[1], Elsa Cardoso[2] and João Oliveira[3]

[1]ISCTE-IUL, Lisbon, Portugal
rfcfa@iscte-iul.pt
[2]ISCTE-IUL, and CIES-ISCTE, Lisbon, Portugal
elsa.cardoso@iscte-iul.pt
[3]ISCTE-IUL, Centro de Investigação em Ciências da Informação, ISTAR-IUL, and Instituto de Telecomunicações, Lisboa, Portugal
joao.p.oliveira@iscte-iul.pt

Abstract Technology has revolutionized the education system. Many tools such as Learning Management Systems (LMS) were developed to enhance the learning process. With this new technology, teachers and universities can explore options otherwise difficult to implement. Keeping students engaged is one of the biggest challenges that educational institutions face. Students' motivation, engagement, and performance can be affected by using LMS. Strategies like self-regulated learning, gamification, and real-time at-risk student detection can be more easily implemented. The analysis of the effects of LMS on learning is made in form of a systematic literature review (SLR). 33 studies published after 2017 were extracted for full-text analysis.

Keyword LMS, Learning Management System, Education, Student, Motivation, Engagement, Performance.

1 Introduction

In the last decades, with the appearance of new technologies, all areas of society suffered a massive change, including the area of education (Hajar et al., 2021; Oguguo et al., 2021; Verawati et al., 2022). To intensify the changes brought to education, due to the covid-19 pandemic, online learning was forced and both universities and teachers had to find a way to improve students' engagement as the interaction between them declined (Ginige & Vanderwall, 2022). Although online learning has great accessibility, scalability, and flexibility (Kittur et al., 2022), it also has a big challenge: not increasing the dropout rates since it makes students feel burdened and unaided (Husni et al., 2022). Keeping students engaged is essential since engagement is closely related to the motivation to be involved and committed (Ustun et al., 2021). It is important for the student to participate, as high participation leads to both high engagement and high performance, and it leads to high levels of learning (Avcı & Ergün, 2022).

Learning management systems (LMS) are essential for the good functioning of online learning (Prabowo et al., 2022). At first, LMSs were simple web pages that contained information about the syllabus, today, they are more sophisticated and enable communication between students and teachers as well as objective assessment and analysis of students' performance (Zhang et al., 2020). They can provide greater insight into how students study and learn (Avcı & Ergün, 2022), foster better communication between students and teachers, and establish more beneficial academic goals (Oguguo et al., 2021).

Learning analytics is a promising area of research that supports teaching and learning. It is especially used with LMS since they generate enormous amounts of data (Ismail et al., 2021; Maraza-Quispe et al., 2021) that may affect students' development and effectiveness (Kittur et al., 2022). The use of LMS with the help of learning analytics provides countless opportunities to enhance students' performance (Fernando Raguro et al., 2022). Even though learning analytics is still in the early steps (Chen & Cui, 2020; Ismail et al., 2021), it gives countless opportunities to address previous problems associated with the use of online learning and LMS platforms such as the lack of engagement, the increasing drop-out ratios, and the lack of motivation (Fahd et al., 2021; Husni et al., 2022; Liz-Dominguez et al., 2022), and helps synthesize students' feedback (Winstone et al., 2021) as well as teachers to track and plan around students' needs through predictive models that can identify the need for interventions during the learning process (Tamada et al., 2021).

This paper aims to do a systematic literature review of how LMS can affect students' performance, motivation, and engagement including an analysis of possible solutions to better enhance students' learning experience and solve many problems in online learning.

The remainder of this paper is structured as follows: Section 2 provides a description of the theoretical background. Section 3 explores the methodology used in this paper. Section 4 reports on the findings of the review. Finally, Section 5 presents the conclusions and a discussion on the limitations of this review.

2 Theoretical background

LMSs are web-based applications that provide students and teachers tools to help with students' learning, including course materials, forums, and quizzes. It can also be used for students to deliver assignments and for teachers to evaluate them and record their grades (Chen & Cui, 2020). LMSs have also been referred to as learning platforms, distributed learning systems, course management systems, and instructional management systems (Oguguo et al., 2021). LMSs are mainly used as an application for students to access materials for lectures, discussions, and assessments in addition to facilitating interactions between teachers and students online (Oguguo et al., 2021). In addition, LMSs can use plug-ins or add-ons to benefit from data generated by students' use. Fig. 2.1 showcases, through a conceptual model, several possible interactions between students and teachers while using the LMSs, as well as the possibility to store data generated from the said interactions in their database.

Some examples of popular LMSs used by universities are Moodle, Blackboard, WebCT, Canvas, Schoology, Edmodo, ATutor, Chisimba, and others (Sanusi et al., 2019; Zhang et al., 2020).

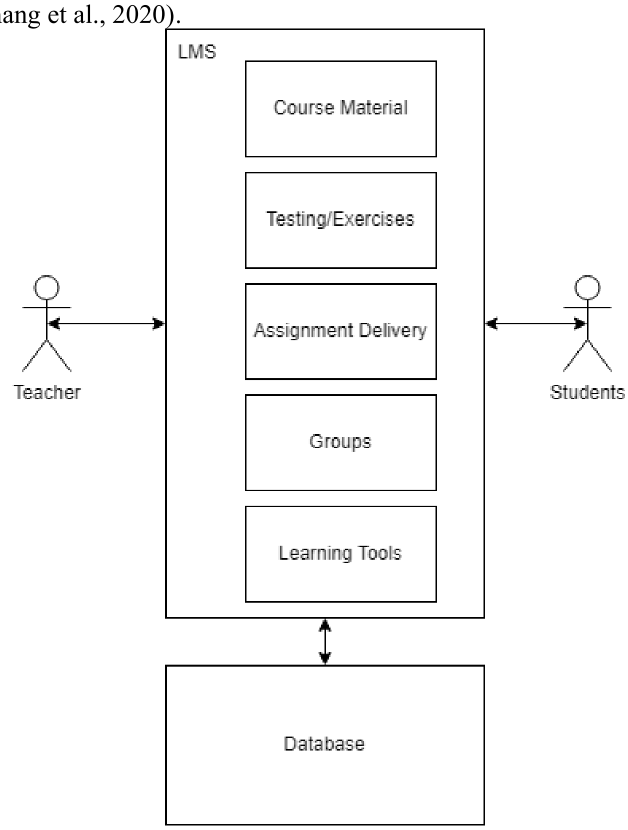

Fig. 2.1. LMS Conceptual Model

3 Methodology

The methodology used in this paper was the Systematic Literature Review (SLR). Fig. 3.1 showcases the phases of development of this SLR, based on the guidelines set by Kitchenham (2004).

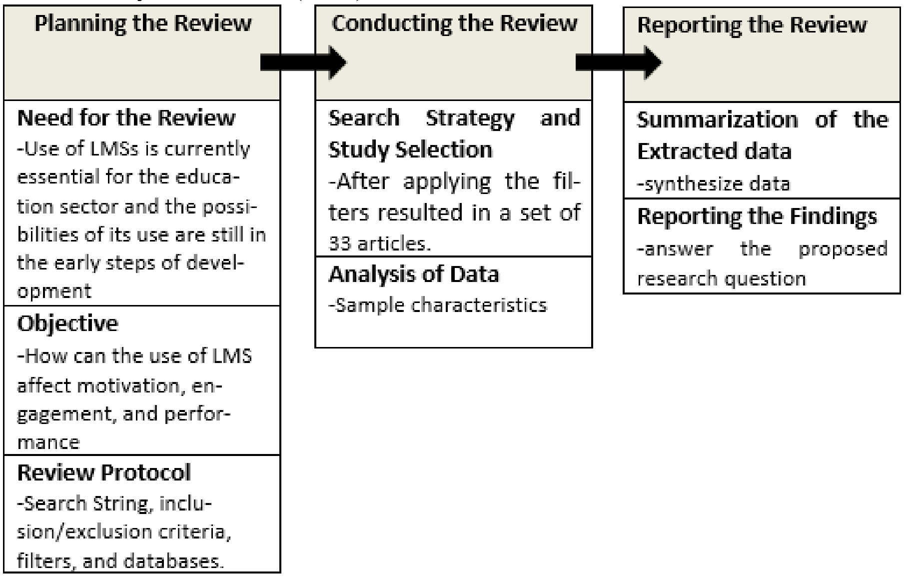

Fig. 3.1. Phases of the SLR

3.1 Identification of the need for a review

Nowadays, LMSs are essential for the educational sector since they remove some boundaries of traditional learning, such as time and space (Ustun et al., 2021), while opening the door to other types of learning such as online learning (Prabowo et al., 2022). With the use of the LMS teachers can have a deeper insight into the learning paths of students (Avcı & Ergün, 2022). The amount of data that one produces while using an LMS is significant and it can be used to improve the learning process (Fernando Raguro et al., 2022; Ismail et al., 2021; Maraza-Quispe et al., 2021). However, the effective use of data mining in the educational sector is still at an early stage (Ismail et al., 2021).

Emotions are important in learning and teaching (Bulut Özek, 2018). Their motivation and engagement usually are related to academic performance (Avcı & Ergün, 2022; Ustun et al., 2021).

Therefore, this study aims to identify how can the use of LMSs affect the motivation, engagement, and performance of students.

3.2 Objective of the review

This paper's main objective is to answer the following research question:
RQ. How can the use of LMSs impact students' motivation, engagement, and performance?

3.3 Review Protocol

Following the theme of this paper, in order to answer the research question, the following search string was identified:
("LMS" OR "Learning Management System") AND "Student" AND ("Motivation" OR "Engagement" OR "Performance").

Table 3.1. Description of inclusive and exclusive criteria

Inclusive Criteria	Scientific papers in conferences or journals Written in English Full-text availability Published after 2017
Exclusion Criteria	Nonscientific papers Not written in English Full-text not available Published before 2017

3.4 Search Strategy and Study Selection

For the study selection, done in October of 2022, it was chosen the database Scopus. For the first filter, it was applied an automatic filter of the title, abstract, and keywords. In the second filter, it was also applied an automatic filter of the title. At last, the third filter was a manual filter of the studies considering the set of inclusive and exclusive criteria displayed in Table 3.2. For the studies to be a part of the analysis they had to follow some criteria. They must be in English, the publishing year must be after 2017, they must be from either a conference paper or an article, and they had to be accessible.

The study selection resulted in 33 relevant studies for analysis.

Table 3.2. Stages of the Studies Selection Process

Database	Initial	1st Filter	2nd Filter	3rd Filter
Scopus	15216	1924	57	**33**

3.5 Analysis of The Literature

In the end, after the selection process was conducted, the sample comprises 33 studies. The studies were analyzed to summarize information and to answer the research question.

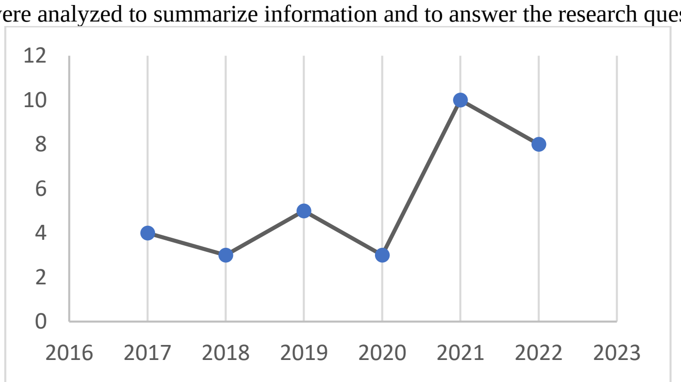

Fig 3.2. Distribution of the selected articles by year

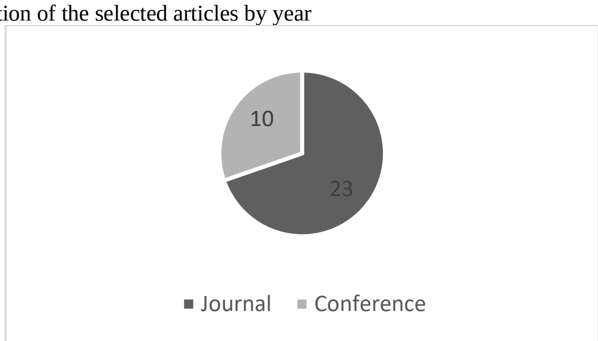

Fig 3.3. Distribution of selected journal and conference articles.

Even though there was a date criterion for collecting articles after 2017, the articles present in the sample that were published in the last two years are 18 out of the 33 total studies, see Fig. 3.2 (note that 2022 only reflects the studies published until October, when this research was conducted). Of the 33 studies 23 of them are published in journals, representing around 70% of the studies (see Fig. 3.3).

4 Conducting the Review

This section presents a summarization of the extracted data and discusses the findings of the SLR.

4.1 Summarization of Extracted Data

The analysis of the sample of studies enabled the identification of six main themes: Motivation, Engagement, Performance, Predictive Models, Gamification, and LMS Data Analysis. Table 4.1 illustrates the distribution of studies along the six main themes identified.

Table 4.1. References for Each Theme Identified.

Themes	Studies References	Total
Motivation	Barua et al. (2019); Bulut Özek (2018); Ginige & Vanderwall (2022); Husni et al. (2022); Ismail et al. (2021); Kittur et al. (2022); Saputro et al. (2019) Ustun et al. (2021)	8
Engagement	Avcı & Ergün (2022); Barua et al. (2019); Fernando Raguro et al. (2022); Ginige & Vanderwall (2022); Henrie et al. (2018); Husni et al. (2022); Ismail et al. (2021); Kittur et al. (2022); Mckay & Young (2017); Nizam Ismail et al. (2019); Prabowo et al. (2022); Sanusi et al. (2019); Saputro et al. (2019); Swart (2017); Tamada et al. (2021); Ustun et al. (2021); Winstone et al. (2021)	17
Performance	Avcı & Ergün (2022); Chen & Cui (2020); Conijn et al. (2017); Fahd et al. (2021); Hajar et al. (2021); Liz-Dominguez et al. (2022); Maraza-Quispe et al. (2021); Mckay & Young (2017); Mwalumbwe & Mtebe (2017); Oguguo et al. (2021); Prestiadi et al. (2021); Riestra-González et al. (2021); Shayan & van Zaanen (2019); Smarr & Schirmer (2018); Tamada et al. (2021); Verawati et al. (2022); Zhang et al. (2020)	17
Predictive Models	Chen & Cui (2020); Conijn et al. (2017); Fahd et al. (2021); Fernando Raguro et al. (2022); Liu et al. (2020); Liz-Dominguez et al. (2022); Maraza-Quispe et al. (2021); Riestra-González et al. (2021); Shayan & van Zaanen (2019); Tamada et al. (2021); Zhang et al. (2020)	12

Gamification	Prabowo et al. (2022); Saputro et al. (2019)	2
LMS Data Analysis	Avcı & Ergün (2022); Barua et al. (2019); Bulut Özek (2018); Chen & Cui (2020); Conijn et al. (2017); Fahd et al. (2021); Fernando Raguro et al. (2022); Hajar et al. (2021); Henrie et al. (2018); Husni et al. (2022); Ismail et al. (2021); Kittur et al. (2022); Liu et al. (2020); Liz-Dominguez et al. (2022); Maraza-Quispe et al. (2021); Mckay & Young (2017); Mwalumbwe & Mtebe (2017); Nizam Ismail et al. (2019); Prestiadi et al. (2021); Riestra-González et al. (2021); Sanusi et al. (2019); Shayan & van Zaanen (2019); Smarr & Schirmer (2018); Swart (2017); Tamada et al. (2021); Ustun et al. (2021); Verawati et al. (2022); Winstone et al. (2021); Zhang et al. (2020)	29

4.2 Report of the Findings

RQ. How can the use of LMSs impact students' motivation, engagement, and performance?

Nowadays the use of LMS is essential for online learning to work (Prabowo et al., 2022) but also for traditional learning (Ustun et al., 2021) and blended learning (both online and face-to-face) (Sanusi et al., 2019). It offers possibilities to solve problems found in learning, such as rising dropout rates, declining motivation, and engagement, and, subsequently, declining performance/learning success (Avcı & Ergün, 2022; Ginige & Vanderwall, 2022; Tamada et al., 2021; Ustun et al., 2021). According to Husni et al. (2022), the adoption of a LMS has a positive effect on the motivation, performance, and cognitive retention of students.

Based on Table 4.1, LMS offers the ability to examine data produced by students' digital footprints. As students participate in the learning process, the LMS gathers data about their learning process, which can be used to gain a deeper understanding of students' engagement and motivation, as well as predict their learning outcomes and performance.

Learning Analytics is another opportunity that LMS offers (Liz-Dominguez et al., 2022). The data generated by students' use of LMS platforms can be used to get more insight into their learning process and learning path. For instance, Oguguo et al. (2021) were able to identify that gender is not a significant factor in the use of LMS platforms; Avcı & Ergün (2022) found that students with high participation had both higher performance and higher engagement; and Liz-

Dominguez et al. (2022) identified that various factors impact students learning outcome, from the retaking of the course to the course syllabus. The information must be extracted as quickly as feasible from the learning process to have a better understanding of it and to be able to act upon it (Maraza-Quispe et al., 2021).

Educational Data Mining consists of the application of artificial intelligence and machine learning making it possible by extracting data from the LMS. Predictive models were developed with the primary goal of predicting student performance. The predictions were developed using an analysis of students' log data while using LMS that consisted of students' participation and engagement throughout the learning process, for example, the participation on quizzes, exercises, forums, and so on. The use of this predictive model allows teachers to identify at-risk students and make an intervention to improve their performance (Tamada et al., 2021).

As shown in Table 4.1, several studies were conducted with a performance predictive model. Chen & Cui, (2020) identified that the best features to use are different in each course taking and it should be personalized according to the syllabus content. Mwalumbwe & Mtebe (2017) shows that peer interaction and forum posts have a significant effect on students' performance in Applied Biology courses but when analyzed in the Service and Installation IIT course, exercises and forum posts had a greater impact.

Overall, the various studies that used a performance predictive model arrived at satisfactory results. Most of the studies that predict students' performance found an accuracy between 75-85% (Fahd et al., 2021; Fernando Raguro et al., 2022), and some reached higher results reaching above 90% of accuracy (Liu et al., 2020; Maraza-Quispe et al., 2021; Riestra-González et al., 2021). Zhang et al. (2020) found that between the features File Usage, Forum Usage, Links Usage, and Assignment Uploads, File Usage was the feature that had a higher correlation with grades.

Tamada et al. (2021) made an early prediction model using Moodle log data that attempted to predict if students will fail at 20%, 40%, and 60% of course completion, providing the potential for early identification of students at risk of failing. Additionally, it was demonstrated that tree-based algorithms had a better performance in these predictions, meaning that it is easier to interpret the results as well as comprehend why students end up failing or dropping out. It was found that the student's involvement and participation in the learning process, i.e., whether they participate in the assignments, exercises, and quizzes, has the biggest influence on their achievement.

Furthermore, Fahd et al. (2021) concluded that real-time identification of at-risk students through their interactions on the LMS platform works in a practical learning environment. Therefore, predictive models may be a viable way to address potential issues and provide students with a more personalized learning experience.

According to Ustun et al. (2021), students' engagement is related to their motivation of staying committed to the course along with their feeling of belonging to a community. Furthermore, they need to be comfortable with using LMS to take advantage of it, otherwise, they do not use all the possible functionalities available. This idea is emphasized by Bulut Özek (2018) that considers learning and teaching emotional processes, i.e., emotions take an important part in the learning process.

Gamification is one of the possible solutions to improve students' motivation and engagement (Prabowo et al., 2022). Saputro et al. (2019) compared two groups of students, one that used a gamified LMS platform and the other that used an LMS platform without the gamification framework. The result was that the group of students that used the gamified LMS platform had better results and a higher success rate. The study concluded that gamification is indeed one of the possible solutions allowed by LMSs to improve students' learning. The principles of gamification might also develop self-regulated strategies, as the establishment of goals and increased motivation leads to the use of self-regulated strategies.

Chen & Cui (2020) identifies that LMS can also improve students' engagement by influencing them to use self-regulated learning strategies. A student's self-regulated learning process consists of the clarification of tasks, setting goals and making plans, adopting strategies to complete the goals and plans, and making an evaluation of the results that the previous steps generated. The communication between students and teachers might be enhanced using an LMS, as well as the availability of more learning resources, enabling them to attain better learning outcomes. High participation is directly connected with students' engagement, so the implementation of activities during the learning process of the student is essential for their success (Avcı & Ergün, 2022). Hence students need to be stimulated by interesting learning contexts and resources. Moreover, Swart, (2017) found that the students who completed at least 50% of online reflective self-assessments had better results, with 100% of the students passing in 2014 and 91% in 2015. Students that completed less than 50% of the online reflective self-assessments had the worst results, having a 78% success rate in 2014 and 50% in 2015.

Kittur et al. (2022) analyzed the time spent by students on the LMS platforms. The time they spent doing quizzes, assignments, discussions, and forums among others, with the objective of observing how the times changed during the duration of the course. They proposed three levels of engagement, "High", "Med", and "Low" and identified that the number of students that reached "High" levels of engagement did not happen as often as the other two, so it was not a good indicator to see if the student would fail or dropout or complete the course. Despite that, the use of "Med" and "Low" levels of engagement proved to be a good indicator of completion of the course, and of identifying if the students were at risk of dropping out or failing the course so teachers could be able to intervene.

According to Winstone et al. (2021) feedback makes planning and tracking easier for students, but usually, it is not given satisfactorily. Students often find it hard to understand its meaning and it leads to not acting upon it. While this is not a problem directly connected to LMS, it provides a couple of tools to help solve it. It enables students to access all the feedback synthesized, in addition to facilitating planning.

The time in which students work on their learning process is also important. Not so much the time of the day they start it, but the students' social jet lag. Social jet lag is the difference between when a student starts the learning process and their individual circadian rhythm. Smarr & Schirmer (2018) found that social jet lag is correlated with the performance of students, for instance, night owls (students that work in later stages of the day) usually have an increased social jet lag. The time of the day they worked on the learning process during class days and non-class days had the biggest difference out of all the other students.

Ismail et al. (2021) identified that there are factors that greatly impact the engagement of students during the use of LMS. They are the involvement of the teacher, the design of the LMS: the behavior of the student; the design of the learning; the self-motivation and motivation level of the student; the monitoring made during the learning process; the learning resources, and the student satisfaction towards the LMS. It also identified the disadvantages of using LMS. The major drawback is that the LMS does not record students' emotions or struggles during the learning process. The inability to use the LMS to its full extent leaves both teachers and students confused concerning its functionalities and issues like students' procrastination might happen; for example, students may wait until the deadline to deliver the assignments and exercises. The only way found in the studies to interpret students' emotions during the learning process is by using webcams to detect them (Bulut Özek, 2018), which only works in online classes, with webcams turned on.

Furthermore, learning actions like forums and quizzes help students keep their engagement throughout the whole learning process. The capability of interacting with other students and to keep testing their knowledge at any time enables students with self-regulated learning skills to improve their learning outcomes. In addition, virtual simulation can be used on the LMS platforms to improve engagement and performance, especially in science, technology, engineering, and mathematics courses (Verawati et al., 2022).

For LMSs to work, it is essential to adopt strategies like gamification and self-regulated strategies to maintain or increase the motivation and engagement of students. One factor mentioned in all the selected studies is that learning comes from the student. The LMS can enhance it and help apply strategies to maintain and improve engagement, but in the end, success comes from the students.

5 Conclusion

The development of LMSs changed the educational sector. The implications of the use of LMSs on students' learning processes are discussed in this SLR. To this end, 33 articles published since 2017 were analyzed.

It was identified that the LMS is a tool that offers many opportunities to improve students' learning. It enables the use of self-regulated learning strategies, gamification, artificial intelligence, and learning analytics, directly impacting the motivation, engagement, and performance of students.

A LMS needs to be well-designed to keep both students and teachers motivated to use it. It also needs to be designed with its use in mind, i.e., teachers and students need to know how to use it to its full potential. It is also important to recognize that depending on the course, different types of learning content or methodologies might be useful as well as the most important features for performance predictions.

It was also recognized that even though LMS facilitates the improvement of students' motivation, engagement, and performance, it ultimately depends on both teachers and students. The quality of the teaching and learning materials is an important factor to keep students engaged in the learning process.

Reflecting on the limitations of this study, although the SLR methodology was followed, only articles from one database were selected, which may have introduced biases.

One aspect that deserves further investigation is related to the evaluation of student performance. In the selected studies, performance is often based on students' final grades and whether they failed or passed the unit course. It does not reflect what the learning outcome was, nor what information the students learned. It might be interesting to look at the actual learning of the students instead of their grades.

References

Avcı, Ü., & Ergün, E. (2022). Online students' LMS activities and their effect on engagement, information literacy and academic performance. *Interactive Learning Environments*, *30*(1), 71–84. https://doi.org/10.1080/10494820.2019.1636088

Barua, P. D., Zhou, X., Gururajan, R., & Chan, K. C. (2019). Determination of Factors Influencing Student Engagement Using a Learning Management System in a Tertiary Setting. *Proceedings - 2018 IEEE/WIC/ACM International Conference on Web Intelligence, WI 2018*, 604–609. https://doi.org/10.1109/WI.2018.00-30

Bulut Özek, M. (2018). The effects of merging student emotion recognition with learning management systems on learners' motivation and academic achievements. *Computer Applications in Engineering Education*, *26*(5), 1862–1872. https://doi.org/10.1002/cae.22000

Chen, F., & Cui, Y. (2020). Utilizing student time series behaviour in learning management systems for early prediction of course performance. *Journal of Learning Analytics*, *7*(2), 1–17. https://doi.org/10.18608/JLA.2020.72.1

Conijn, R., Snijders, C., Kleingeld, A., & Matzat, U. (2017). Predicting student performance from LMS data: A comparison of 17 blended courses using moodle LMS. *IEEE Transactions on Learning Technologies*, *10*(1), 17–29. https://doi.org/10.1109/TLT.2016.2616312

Fahd, K., Miah, S. J., & Ahmed, K. (2021). Predicting student performance in a blended learning environment using learning management system interaction data. *Applied Computing and Informatics*. https://doi.org/10.1108/ACI-06-2021-0150

Fernando Raguro, M. C., Carpio Lagman, A., Abad, L. P., & Ong, P. L. S. (2022). Extraction of LMS Student Engagement and Behavioral Patterns in Online Education Using Decision Tree and K-Means Algorithm. *ACM International Conference Proceeding Series*, 138–143. https://doi.org/10.1145/3512353.3512373

Ginige, T. N. D. S., & Vanderwall, S. T. (2022). Effective online learning management system to improve and enhance the online learning and student engagement experience. *ACM*

International Conference Proceeding Series, 95–100. https://doi.org/10.1145/3546157.3546172

Hajar, M., Adil, J., & Ali, Y. (2021). PREDICTING FACTORS AFFECTING STUDENT'S PERFORMANCE IN A LEARNING MANAGEMENT SYSTEM. *Indian Journal of Computer Science and Engineering*, *12*(6), 1771–1779. https://doi.org/10.21817/indjcse/2021/v12i6/211206015

Henrie, C. R., Bodily, R., Larsen, R., & Graham, C. R. (2018). Exploring the potential of LMS log data as a proxy measure of student engagement. *Journal of Computing in Higher Education*, *30*(2), 344–362. https://doi.org/10.1007/s12528-017-9161-1

Husni, N. H. A., Jumaat, N. F., & Tasir, Z. (2022). Investigating Student's Cognitive Engagement, Motivation and Cognitive Retention in Learning Management System. *International Journal of Emerging Technologies in Learning*, *17*(9), 184–200. https://doi.org/10.3991/ijet.v17i09.29727

Ismail, S. N., Hamid, S., Ahmad, M., Alaboudi, A., & Jhanjhi, N. (2021). Exploring students engagement towards the learning management system (LMS) using learning analytics. *Computer Systems Science and Engineering*, *37*(1), 73–87. https://doi.org/10.32604/CSSE.2021.015261

Kitchenham, B. (2004). Procedures for performing systematic reviews. *Keele, UK, Keele University*, *33*(2004), 1-26.

Kittur, J., Bekki, J., & Brunhaver, S. (2022). Development of a student engagement score for online undergraduate engineering courses using learning management system interaction data. *Computer Applications in Engineering Education*, *30*(3), 661–677. https://doi.org/10.1002/cae.22479

Liu, W., Xu, W., Zhan, X., Liu, W., & Cheng, W. (2020). Student performance prediction by LMS data and classroom videos. *15th International Conference on Computer Science and Education, ICCSE 2020*, 535–539. https://doi.org/10.1109/ICCSE49874.2020.9201684

Liz-Dominguez, M., Llamas-Nistal, M., Caeiro-Rodriguez, M., & Mikic-Fonte, F. (2022). LMS Logs and Student Performance: The Influence of Retaking a Course. *IEEE Global Engineering Education Conference, EDUCON*, *2022-March*, 1970–1974. https://doi.org/10.1109/EDUCON52537.2022.9766691

Maraza-Quispe, B., Valderrama-Chauca, E. D., Cari-Mogrovejo, L. H., & Apaza-Huanca, J. M. (2021). Predictive Model of Student Academic Performance from LMS data based on Learning Analytics. *ACM International Conference Proceeding Series*, 13–19. https://doi.org/10.1145/3498765.3498768

Mckay, D. B., & Young, B. J. (2017). Engagement of ESL Students with a Science Course Delivered in English with an Emphasis on Assessment Using a Learning Management System. *International Journal of Learning*, *3*(2), 95–100. https://doi.org/10.18178/IJLT.3.2.95-100

Mwalumbwe, I., & Mtebe, J. S. (2017). Using learning analytics to predict students' performance in moodle learning management system: A case of Mbeya University of science and technology. *Electronic Journal of Information Systems in Developing Countries*, *79*(1), 1–13. https://doi.org/10.1002/j.1681-4835.2017.tb00577.x

Nizam Ismail, S., Hamid, S., & Chiroma, H. (2019). The utilization of learning analytics to develop student engagement model in learning management system. *Journal of Physics: Conference Series*, *1339*(1). https://doi.org/10.1088/1742-6596/1339/1/012096

Oguguo, B. C. E., Nannim, F. A., Agah, J. J., Ugwuanyi, C. S., Ene, C. U., & Nzeadibe, A. C. (2021). Effect of learning management system on Student's performance in educational measurement and evaluation. *Education and Information Technologies*, *26*(2), 1471–1483. https://doi.org/10.1007/s10639-020-10318-w

Prabowo, H., Yuniarty, & Ikhsan, R. B. (2022). Student Engagement Mechanism of Online Learning: The Effect of Service Quality on Learning Management System. *International*

Journal on Informatics Visualization, *6*(3), 681–687. https://doi.org/10.30630/joiv.6.3.1263

Prestiadi, D., Wiyono, B. B., & Mustabsyiroh, N. (2021). Analysis of online learning media at SIPEJAR as a learning management system (LMS) during the Covid-19 pandemic in improving student performance. *Proceedings - 2021 7th International Conference on Education and Technology, ICET 2021*, 74–80. https://doi.org/10.1109/ICET53279.2021.9575115

Riestra-González, M., Paule-Ruíz, M. D. P., & Ortin, F. (2021). Massive LMS log data analysis for the early prediction of course-agnostic student performance. *Computers and Education*, *163*. https://doi.org/10.1016/j.compedu.2020.104108

Sanusi, N. M., Kamalrudin, M., & Mohtar, S. (2019). Student engagement using learning management system in computer science education. *International Journal of Recent Technology and Engineering*, *8*(2 Special), 743–747. https://doi.org/10.35940/ijrte.B1121.0982S1119

Saputro, R. E., Salam, S., Zakaria, M. H., & Baihaqi, W. M. (2019). The effectiveness of the gamified LMS platform to increase students' motivation in online courses. *International Journal of Advanced Trends in Computer Science and Engineering*, *8*(1.5 Specia), 327–332. https://doi.org/10.30534/ijatcse/2019/5481.52019

Shayan, P., & van Zaanen, M. (2019). Predicting student performance from their behavior in learning management systems. *International Journal of Information and Education Technology*, *9*(5), 337–341. https://doi.org/10.18178/ijiet.2019.9.5.1223

Smarr, B. L., & Schirmer, A. E. (2018). 3.4 Million real-world learning management system logins reveal the majority of students experience social jet lag correlated with decreased performance. *Scientific Reports*, *8*(1). https://doi.org/10.1038/s41598-018-23044-8

Swart, A. J. (2017). Using reflective self-assessments in a learning management system to promote student engagement and academic success. *IEEE Global Engineering Education Conference, EDUCON*, 175–180. https://doi.org/10.1109/EDUCON.2017.7942844

Tamada, M. M., Giusti, R., & de Magalhaes Netto, J. F. (2021). Predicting Student Performance Based on Logs in Moodle LMS. *Proceedings - Frontiers in Education Conference, FIE*, *2021-Octob*. https://doi.org/10.1109/FIE49875.2021.9637274

Ustun, A. B., Karaoglan Yilmaz, F. G., & Yilmaz, R. (2021). Investigating the role of accepting learning management system on students' engagement and sense of community in blended learning. *Education and Information Technologies*, *26*(4), 4751–4769. https://doi.org/10.1007/s10639-021-10500-8

Verawati, N. N. S. P., Ernita, N., & Prayogi, S. (2022). Enhancing the Reasoning Performance of STEM Students in Modern Physics Courses Using Virtual Simulation in the LMS Platform. *International Journal of Emerging Technologies in Learning*, *17*(13), 267–277. https://doi.org/10.3991/ijet.v17i13.31459

Winstone, N., Bourne, J., Medland, E., Niculescu, I., & Rees, R. (2021). "Check the grade, log out": students' engagement with feedback in learning management systems. *Assessment and Evaluation in Higher Education*, *46*(4), 631–643. https://doi.org/10.1080/02602938.2020.1787331

Zhang, Y., Ghandour, A., & Shestak, V. (2020). Using Learning Analytics to Predict Students Performance in Moodle LMS. *International Journal of Emerging Technologies in Learning*, *15*(20), 102–114. https://doi.org/10.3991/ijet.v15i20.15915