e-Learning Interactions and Academic Outcomes: an Analysis of Undergraduates in Sri Lanka

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Abstract: The shift to online teaching and learning following the onset of the COVID-19 pandemic resulted in a large increase in the usage of online learning platforms. Student interactions with these platforms provide an important source of information on student progress on a course during periods of distance learning. However, in resource constrained settings where students face difficulties in accessing stable and quality internet, it is unclear to what extent interactions with the learning platform influence academic outcomes, especially for programmes that were not originally intended to be delivered online. This study makes use of data on four cohorts of undergraduate students at the University of Moratuwa, where each cohort was exposed to different periods of online teaching and learning. The data covers interactions with Moodle course pages and assessment marks for multiple courses with diverse subject contents offered in two faculties. Interactions with the learning platform are measured using clicks on different types of objects on the course page as well as the distribution of clicks over the course of semester. To account for the confounding effect of prior ability on the relationship between learning platform interactions and academic outcomes, we also use results from courses that the students have taken a priori. We find that while the switch to online teaching and learning led to a dramatic increase in the level of student interactions with the learning platform, the level of interaction has remained above the pre-COVID levels even after resuming on-site, face-to-face delivery. While differences among the subjects and cohorts exist, results from a multiple regression model suggest that the association with certain types of learning platform interactions and academic outcomes are significant even after controlling for prior ability and differences in course design. Specifically, the volume and consistency of access both improve outcomes with the timing of clicks more strongly associated with the final examination mark whereas the type of content clicked on is more associated with continuous assessment marks. The findings have important implications for the continued adoption of blended learning methods and course design for the programmes under study.

Keywords: e-Learning Interactions, Student Behaviour, Learning Analytics, Online Learning

1. Introduction

The shift to online teaching and learning following the onset of the COVID-19 pandemic resulted in a large increase in the usage of online learning platforms within the higher education sector. Education providers who had previously made little or no use of learning management systems (LMS) were forced to switch to online delivery within relatively short periods. The transitions ranged from merely changing the delivery of a lecture from on-site to a video-conferencing tool to redesigning courses to encourage more interactive learning in an online environment (Brancaccio-Taras et al, 2021; Pagoto et al, 2021; Lee et al, 2021; Means and Neisler, 2020; Rapanta et al, 2020).

The Sri Lankan state higher education sector was no exception. While all educational institutions closed on 12 March 2020, it is estimated that by June 2020, almost all universities had switched to online education (Hayashi et al, 2020). This is despite substantial challenges faced in terms of lack of adequate infrastructure (including devices and internet connectivity) among students and limited prior exposure to online education among both staff and students (World bank, 2020). Key measures taken to facilitate the transition included the provision of free access to university web servers by internet service providers and free access to a video-conferencing solution via university web servers.

Despite the rapid transition to online teaching and learning, it has been more challenging to ensure the continuous engagement and achievement of learning outcomes for courses that were not originally designed for online delivery among students who were not prepared for this mode of learning. Student interactions with learning management platforms provide an important source of information on student progress on a course during periods of distance learning. However, in resource constrained settings where students and courses were not prepared for online delivery, it is unclear as to how well these student interactions can predict learning outcomes. For instance, all learning activities cannot be monitored through the LMS even for activities implemented through the system (for example, if students share resources shared on the LMS with each other using other means such as social media or email).

Indeed, while there is a body of work on education and learning analytics, much of this work focuses on courses that were designed for online learning (for example, Ruipérez-Valiente, Munoz-Merino and Kloos (2018), Grandzol and Grandzol (2010)). The experience of the Sri Lankan state universities (and possibly many others internationally) following the onset of the pandemic was different, essentially following a form of blended learning with face-to-face synchronous interactions with the lecturer (via video conferencing) as the key instructional element supplemented (in some cases) with additional learning resources and activities on the LMS. Three years on, we are now well-placed to take stock of the unprecedented transition brought on by the pandemic and assess the teaching and learning experience taking place during this period.

As such, this paper studies the relationship between student interactions with the LMS and academic outcomes based on the experiences of one of the state universities in Sri Lanka. This study makes use of data on four cohorts of undergraduate students at the University of Moratuwa, where each cohort was exposed to different periods of online teaching and learning. The data covers interactions with the Moodle course pages and assessment marks for four first- and second-year courses with diverse subject contents offered in two different faculties. By using data on cohorts taking the subjects online as well as on-site, we can see both how interactions with the LMS changed following the switch to online education as well as identify if there are differences in the way that these interactions influenced academic outcomes in the two periods.

The rest of the paper is organized as follows: Section 2 discusses some of the related literature. Section 3 describes the data and methods used. Section 4 presents the results and the final section discusses the implications of the results and concludes.

2. Related Work

The adoption of learning management systems like Moodle and Blackboard to facilitate learning has generated a vast amount of data resulting in the emergence of the field of learning analytics (Ferguson and Shum, 2012). While there is also a growing body of work based on the experience of the switch to online teaching and learning as a consequence of the Covid-19 pandemic, much of this work, which examines the use of online teaching and learning as an emergency tool, is based on survey data or qualitative research methods to analyse student and faculty perspectives on this transition (see Lee et al (2021) for a review of this literature). However, given the quantitative nature of this study, in this section we review the learning analytics literature most relevant to this paper.

LMS usage statistics provide a wealth of insights about student learning behaviours including logs containing detailed information on when a student accessed the LMS and which components they interacted with. Commonly constructed variables for measuring LMS usage include total time spent on the LMS, frequency of access, total visits to the LMS, etc. Several studies have found that even such simple measures can help predict student performance (Ulfa and Fatawi, 2021; Damianov et al, 2009; Vengross and Bourbeau, 2006,). Other researchers have also considered the consistency with which a student may access the LMS and find that hit consistency is a strong (if not stronger) predictor of student success (Bitkimirov and Klassen, 2008; Baugher, Varanelli and Weisbord, 2003). Crampton, Ragusa and Cavanagh (2012) take the analysis a step further to also find that the diversity of resources accessed by students also has a positive impact on grades.

However, LMS logs allow for more nuanced insights than just total clicks or time spent on the system. It is also possible to identify the types of tools that encourage the most interactivity among the students, which could be very informative in the process of improving course design. For instance, reading and posting of messages on course forums have been found to be significant in predicting student outcomes by Coldwell et al. (2008), MacFayden and Dawson (2010) and Zacharis (2015). More recent work by Ruipérez-Valiente et al (2018) uses the learning analytics support provided by the Khan Academy to consider an array of more sophisticated student behaviour-related variables into a multiple regression model to predict learning gains. These variables include the percentage of videos completed, the time spent on solving exercises or watching videos, the number of optional activities accessed etc. While several of these variables are found to be important, the authors highlight that the pre-test score is a key predictor of learning gains.

A related strand of research examines the importance of different types of interactions in influencing student outcomes, including learner-learner, learner-instructor and learner-content interactions. Li et al (2022) use a quasi-experimental design to assign students to two groups with varying types of interactions in an online environment and find that learner-learner and learner-content interactions were the most significant predictors of student performance and student satisfaction. Other studies make use of ex-post evaluations to assess the role of different types of interactions by classifying user interactions recorded in the LMS logs (Agudo-Peregrina et al., 2014; Grandzol and Grandzol, 2010). However, the ability to measure inter-personal interactions between students or students and teachers using only the LMS logs is limited, especially in contexts where students and teachers may communicate in other ways such as email, mobile phones or social media (or even face to face if courses are offered in a blended learning mode).

While the scope for the type of information that can be extracted from LMS logs is huge, many studies are constrained in terms of the sample of students studied, limiting the number of variables that can be included in their statistical models. Moreover, the literature is predominantly based on courses that were designed for online or blended learning, an important distinction in the context of this paper where the switch to online learning was an emergency response to the Covid-19 closures of the universities. As such, this paper builds on the available literature to evaluate the effectiveness of LMS-user interactions for understanding student outcomes in this current context, making use of a variety of different courses and multiple cohorts of students.

3. Data and Methods

3.1 Selected Cohorts and Subjects

The study considers four 1st and 2nd year courses followed by four consecutive undergraduate cohorts (intake 2017 to 2020) from two different Faculties in the University. Specifically, the study uses two statistics related subjects offered to 2nd year business students and two subjects (one related to communication skills and the other related to computer operating systems) offered to 1st and 2nd year engineering students. The differences in the nature of the subjects and background of the students (and staff) in terms of readiness for online learning allow us to explore differences in student interactions with the learning platform in greater detail.

The combinations of selected cohorts and courses cover different levels of exposure to online teaching and learning - the earliest cohort considered followed the selected (and all preceding) subjects on-site whereas the later cohorts had followed most of their courses online. It should be noted that even in the earlier periods of on-site delivery, the selected course pages on the learning platform were already being made use of though at different levels, with Moodle being available in both desktop and mobile app versions. For instance, for the earliest cohort of Business students, the Moodle pages were used primarily to share resources such as lecture slides, tutorials and references. Most assessments, formative and summative, were administered physically with hard copy submissions. After the shift to online delivery, the Moodle pages were utilized for much more including submission of assignments, participation in quizzes and interactive learning content, and scheduling of online lectures and discussions. Table 1 summarizes the modes of delivery of the four subjects and cohorts considered for the analysis.

Table 1: Mode of delivery

Faculty	Semester	Cohort			
		2017	2018	2019	2020
Business	3	F2F	F2F	Online	Online
	4	F2F	Online*	Online	F2F
Engineering	2	F2F	F2F	Online	Online
	3	F2F	Online*	Online	Hybrid

Note: F2F refers to face-to-face, on-site delivery

*A few lectures held on-site but mainly (including all assessments) online

The total sample consists of four subjects and 1,010 students (429 business students and 581 engineering students), most of whom are followed for two subjects each.

3.2 Learner interactions with the Moodle pages

For each of the courses offered to each cohort, we use course logs taken from the Moodle course pages to measure student interactions with the learning platform. An alternative source of information is the activity completion log of a course page. However, given that for some of the courses there were no Moodle activities carried out during periods of on-site delivery we do not use this source of information.

We draw from the literature to construct measures of total access frequency and consistency as well as measures of access for specific types of content. Specifically, alongside the count of total clicks, we construct separately the share of clicks made on static (e.g. lecture slides or references) and interactive (e.g. quizzes, assignments, etc.) content, where the remainder consists of clicks made to view the course page or announcements. To study the consistency of access over the course of the Semester, we use the standard deviation of clicks observed during each month of the Semester for each student - a lower standard deviation suggests that the student consistently accesses the course over the entire duration of the Semester. We also compute separately the share of clicks made during the first half and second half of the Semester, where the remainder consists of clicks taking place after the Semester has ended but before the final Examination.

The number of clicks made by students are clearly linked to the design of the Moodle course page; for instance, the number of activities to be completed via the Moodle page. Moreover, the design of the course page could be geared towards encouraging asynchronous learning which would also affect student learning outcomes. Accordingly, the number of activities conducted via the Moodle page is also included as a variable moderating the relationship between learner interactions and academic outcomes.

3.3 Academic outcomes

This study makes use of the continuous assessment (CA) and written examination (WE) marks obtained for the course as the measures of academic outcomes. The CA mark is the aggregate mark from all summative assessments carried out during the semester, while the WE is conducted at the end of the semester.

An additional confounding effect that may be important to this analysis is the ability of the student. Student ability will influence marks obtained on assessments but also influence learning behaviour and interactions with the learning platform. As such, we use results from related courses that students have taken a priori, in a semester preceding the course being studied, to control for this effect.

3.4 Methods

The relationship between learner interactions and academic outcomes are studied using the following model:

$$y_{isft} = \alpha + \beta X_{isft} + \gamma \text{ PriorAbility}_i + \theta_{st} + \delta_{tf} + u_{isft} \quad (1)$$

where the dependent variables considered, y_{isft}, are the CA and WE marks obtained on subject s by student i belonging to cohort t in Faculty f. X_{isft} is the vector of learner interaction variables for each student. To control for differences between subjects, cohorts and faculties, we include θ_{st}, which refers to fixed effects related to a subject offered to a given cohort (including the number of Moodle activities conducted on the Moodle page) and δ_{tf}, which accounts for fixed effects related to a cohort in a given Faculty. u_{isft} refers to an idiosyncratic error term.

4. Results

4.1 Descriptive analysis

Figure 1 shows the distribution of total clicks by mode of delivery across the four subjects using a box plot.

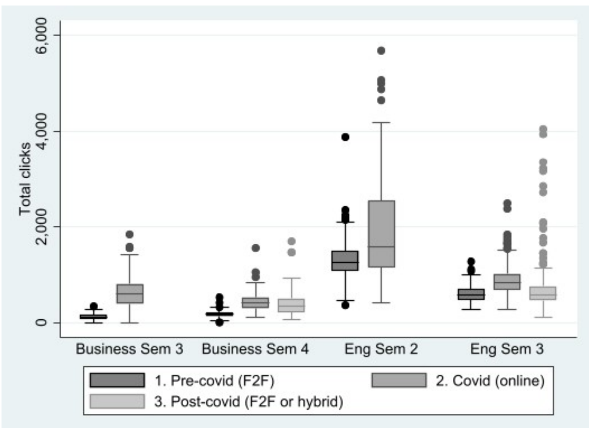

Figure 1: Total clicks by mode of delivery and subject

Note: The Figure shows the box plots of total clicks across the faculties and mode of delivery. The three horizontal lines that form a box in each plot refer to the 25th, 50th, and 75th percentile values; the two horizontal lines appearing at the end of the vertical lines are the adjacent values (most extreme values within 1.5 times the interquartile range of the nearest quartile); the dots refer to any outside values that are higher (lower) than the upper (lower) adjacent value.

The Figure provides several insights. First, the number of clicks in the pre-Covid era is much lower for the courses offered to Business students (in terms of median and quartiles) given that the course pages were primarily used to supplement face-to-face delivery through sharing of additional resources. Among the courses offered to the engineering students, total clicks are much higher, especially for the 2nd semester communication skills subject that had a course page already designed for active online learning. Second, we see the expected increase in clicks during the period of online delivery, across all courses. Third, for the two subjects that we observe in the post-covid return to onsite or hybrid delivery, we see that total clicks remain above the pre-Covid level. This is particularly true for the Business faculty subject where the LMS course page was not heavily utilized pre-Covid. Given the clear differences between the courses from the two faculties, the regression models are computed for the total sample as well as for the two faculties separately.

Figures 2 and 3 present the correlation matrices for the variables considered in the analysis, looking separately at subjects taught on-site and online. The two graphs show some differences in magnitude of correlations for onsite and online delivery but the results are qualitatively very similar. Performance in the assessment (CA, WE or final mark) is positively correlated with clicks of all types and negatively correlated with the standard deviation of clicks. For instance, the correlation coefficient between final mark and total clicks is 0.29 for onsite delivery and 0.43 for online delivery, while the correlation between final mark and the standard deviation of monthly clicks is -0.24 and -0.31 for onsite and online delivery, respectively. The latter result shows that greater consistency is associated with better academic outcomes. We also see a strong positive correlation between the mark obtained in the pre-requisite course and that this mark is also positively associated with LMS interactions (e.g. correlation between marks in the considered course and pre-requisite is 0.7 for onsite delivery, while the correlation between pre-requisite mark and total clicks in the considered course is 0.09). The same is true for the number of activities included in the LMS course page, motivating the use of these two variables as confounders in the regression analysis. Given the similarities of the correlation matrices for online and onsite delivery, the regression analysis considers the full sample of subjects together after allowing for differences in the mean assessment marks before, during and after the period of online teaching and learning.

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Total clicks	(1)	**1.00**										
Click distribution	(2)	-0.27	**1.00**									
Clicks at start of semester	(3)	0.76	0.08	**1.00**								
Clicks in middle of semester	(4)	0.94	-0.35	0.54	**1.00**							
Clicks on static content	(5)	0.40	0.03	0.33	0.43	**1.00**						
Clicks on interactive content	(6)	0.70	-0.09	0.83	0.50	0.14	**1.00**					
Number of activities	(7)	0.61	-0.06	0.82	0.41	0.12	0.90	**1.00**				
Prior ability	(8)	0.09	-0.21	-0.04	0.09	0.02	0.04	-0.01	**1.00**			
WE mark	(9)	0.17	-0.07	0.20	0.09	0.05	0.23	0.18	0.65	**1.00**		
CA mark	(10)	0.20	-0.28	0.02	0.22	0.06	0.08	0.01	0.64	0.56	**1.00**	
Final mark	(11)	0.29	-0.24	0.17	0.26	0.07	0.28	0.20	0.70	0.84	0.83	**1.00**

Figure 2: Correlation matrix – onsite delivery

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Total clicks	(1)	**1.00**										
Click distribution	(2)	-0.17	**1.00**									
Clicks at start of semester	(3)	0.95	-0.22	**1.00**								
Clicks in middle of semester	(4)	0.93	-0.14	0.83	**1.00**							
Clicks on static content	(5)	0.32	-0.28	0.37	0.33	**1.00**						
Clicks on interactive content	(6)	0.97	-0.10	0.91	0.89	0.15	**1.00**					
Number of activities	(7)	0.88	-0.12	0.88	0.76	0.17	0.90	**1.00**				
Prior ability	(8)	0.12	-0.21	0.16	0.14	0.25	0.06	0.11	**1.00**			
WE mark	(9)	0.37	-0.29	0.41	0.35	0.36	0.32	0.34	0.41	**1.00**		
CA mark	(10)	0.34	-0.26	0.38	0.31	0.19	0.33	0.31	0.35	0.59	**1.00**	
Final mark	(11)	0.43	-0.31	0.46	0.40	0.32	0.39	0.39	0.42	0.94	0.83	**1.00**

Figure 3: Correlation matrix - online delivery

4.2 Regression Results

The regression analysis examines how the different measures of LMS interaction are associated with student outcomes after controlling for differences in subjects, cohorts and prior ability. Table 2 shows the results of the regression estimated on the entire sample students, as well as for the business and engineering students separately. Robust standard errors are reported in brackets.

As Table 2 shows, there are both similarities and differences in how the selected explanatory variables are associated with academic outcomes among the two sets of students and two types of assessment considered. The first two columns report the results from estimating the model on the full sample of students. The results suggest that total clicks significantly improve both CA and WE marks, as do prior ability and the share of clicks on static content. The timing and consistency of clicks as well as the share of clicks on interactive content are relatively more important for improving CA marks. However, these results mask considerable differences between the students and subjects in the two faculties. Accordingly, the rest of the section will discuss these disaggregated results in more detail.

Table 2: Relationship between LMS interactions and academic outcomes

	WE mark (Full sample)	**CA mark (Full sample)**	**WE mark**		**CA mark**	
			Business	Eng	Business	Eng
	(1)	(2)	(3)	(4)	(5)	(6)
Total clicks	0.002**	0.001*	0.006**	0.003***	-0.012**	0.004***
	[0.001]	[0.001]	[0.003]	[0.001]	[0.005]	[0.001]
Distribution of clicks	-12.351	-38.247***	-38.007***	-16.296	-34.624*	-74.977***
	[9.122]	[11.840]	[14.318]	[15.074]	[17.785]	[16.372]
Share of clicks in 1st half of Sem	-18.500***	-37.796***	-34.311***	7.569	-66.294***	10.514
	[3.693]	[4.207]	[5.668]	[5.753]	[6.874]	[6.409]
Share of clicks in latter half of Sem	0.344	14.660**	-9.264	11.666**	8.782	10.409
	[4.426]	[5.764]	[6.305]	[5.257]	[8.981]	[6.376]
Share of clicks on static content	14.608**	31.280***	16.999	4.68	45.718***	2.997
	[6.826]	[7.864]	[10.394]	[6.482]	[13.246]	[6.422]
Share of clicks on activities	-8.621*	14.411***	1.753	9.676*	16.610*	17.520***
	[4.416]	[5.288]	[6.958]	[5.463]	[9.551]	[4.751]
	-0.166**	1.297***	-0.268**	-0.159	2.269***	0.567***

	WE mark (Full sample)	CA mark (Full sample)	WE mark		CA mark	
			Business	Eng	Business	Eng
	(1)	(2)	(3)	(4)	(5)	(6)
Number of activities	[0.080]	[0.086]	[0.121]	[0.109]	[0.160]	[0.108]
Prior ability	0.626***	0.437***	0.863***	0.372***	0.594***	0.333***
	[0.031]	[0.031]	[0.038]	[0.034]	[0.050]	[0.036]
N	1792	1790	764	1028	764	1026
R-square	0.507	0.549	0.536	0.374	0.645	0.375

*Note: All regressions control for subject fixed effects and faculty-cohort fixed effects. Robust standard errors in brackets. Significance levels: * 10%, ** 5%, *** 1%*

Among the considered explanatory variables, prior ability has the most consistent impact on academic outcomes, with a larger, positive impact among Business students. For instance, an increase in the mark of the pre-requisite subject by 1, results in an increase of WE marks by 0.8, holding constant the effect of LMS interactions. Among engineering students, the increase is 0.4. Indeed, prior ability is a key confounder in the analysis, increasing the regression r-square by around 20 percentage points and changing the estimated coefficients on LMS interactions significantly (additional results available on request).

The estimated coefficients on the LMS interactions show more variation across the two groups of students and type of assessment considered. Total clicks are significantly and positively associated with both CA and WE marks among the engineering students, and for WE marks among the business students. For example, an additional 100 clicks on the LMS course page is associated with an increase of 0.6 marks in the WE and 1.2 marks in the CA for business students. However, total clicks are negatively associated with CA marks for the business students. The distribution of clicks across the semester (our measure of consistency) is also statistically significant across faculties, with marks decreasing for students with a higher standard deviation in clicks over the semester. In other words, students who access the LMS more consistently record better academic outcomes on average.

In terms of timing of the clicks, having a higher share of clicks at the start of the semester (compared to closer to the written examination) significantly reduces both WE and CA marks among business students, after controlling for consistency of access and other confounders. The timing matters less for the engineering students where the continuous assessments are spread over the entirety of the semester – consequently, the effect of consistency of clicks is also largest for CA marks among these students. On the other hand, the clicks by type of content accessed have a stronger effect on engineering students. More clicks on activities and interactive content significantly increases both CA and WE marks for these students whereas for the business students, it is only the CA mark which is improved. The latter result may point to differences in the type of learning outcomes measured by the CA and WE for these subjects.

The estimated regression models vary in terms of predictive power, depending on the group of students considered - the model can explain more than 50 percent of the variation in WE marks among business students and close to two-thirds of their CA marks. The explanatory power of the model is much lower for the engineering students, just over one third of variation in both CA and WE marks are explained by the model.

5. Conclusion

This paper makes use of data on four undergraduate cohorts from two faculties in the University of Moratuwa, Sri Lanka, to study the relationship between student interactions with the LMS and learning outcomes. The data spans the pre-Covid period of on-site teaching and learning, the Covid period of exclusively online delivery and the post-Covid period where subjects were delivered on-site or through a hybrid model. By considering subjects that were not originally designed for (purely) online delivery and students who may not have been prepared for the same, we are able to add to the literature on the use of online teaching and learning for emergency purposes as well as online learning in general.

The analysis finds that, while the Covid-19 related closures resulted in increased levels of interaction with the LMS, the levels of interaction remain higher than in the pre-Covid period, reflecting an increased level of comfort with online tools for teaching and learning among both staff and students. We also find, consistent with the literature, that there are strong associations between student interactions with the LMS and their learning outcomes. In particular, both the volume and consistency of clicks significantly predict marks in both continuous assessments and end-semester examinations. Depending on the group of students considered (business or engineering), the timing of the clicks and type of click by content accessed also influences grades, with the timing of clicks relatively more important for predicting final examination marks and the type of content clicked on having more explanatory power for predicting continuous assessment marks. While we find that both the prior ability of the student and design of the course page are important confounding factors, they cannot explain away the relationship between LMS interactions and student outcomes. It should be noted that the results presented here are affected by the novice online learner nature of the students, at least in the case of the Business students. As such, there is likely to be additional noise around the LMS interactions observed for these students. While this is accounted for to some extent through the inclusion of the cohort-specific fixed effects, it could still affect the precision of these results. However, it is reassuring that even with this element of noise, we still observe significant associations between the learner interactions and their outcomes.

In all, these results have important implications for current and future usage of online or hybrid learning as the evidence presented suggests that students with low or inconsistent access to the LMS can be flagged for early intervention. Of course, the key to encouraging greater LMS usage among students is better course page design, including more interactive content for students to engage with. Further study of the evolution of course page design over this transition period and investigation of the types of activities that generate the most meaningful student engagement is left for future research.

References

Agudo-Peregrina, Á.F., Iglesias-Pradas, S., Conde-González, M.Á. and Hernández-García, Á., (2014). "Can we predict success from log data in VLEs? Classification of interactions for learning analytics and their relation with performance in VLE-supported F2F and online learning", *Computers in human behavior*, 31, 542-550.

Baugher, D., Varanelli, A., and Weisbord, E., (2003). "Student hits in an internet-supported course: How can instructors use them and what do they mean?", *Decision Sciences Journal of Innovative Education*, 1(2), 159-179.

Biktimirov, E.N. and Klassen, K.J., (2008). "Relationship between use of online support materials and student performance in an introductory finance course". *Journal of education for business*, 83(3), 153-158.

Brancaccio-Taras, L., Mawn, M.V., Premo, J., and Ramachandran, R., (2021). "The Editors' Perspectives on Adjusting STEM Education to the "New Normal" during the COVID-19 Pandemic", *Journal of Microbiology & Biology Education*, 22(1), 22.1.65. https://doi.org/10.1128/jmbe.v22i1.2679

Coldwell, J., Craig, A., Paterson, T. and Mustard, J., (2008). "Online students: Relationships between participation, demographics and academic performance", *Electronic journal of e-learning*, 6(1), 19-28.

Crampton, A., Ragusa, A.T. and Cavanagh, H., (2012). "Cross-discipline investigation of the relationship between academic performance and online resource access by distance education students", *Research in Learning Technology*, 20(1), doi: 10.3402/rlt.v20i0.14430.

Damianov, D.S., Kupczynski, L., Calafiore, P., Damianova, E.P., Soydemir, G. and Gonzalez, E., (2009). "Time spent online and student performance in online business courses: A multinomial logit analysis", *Journal of Economics and Finance Education*, 8(2), 11-22.

Ferguson, Rebecca and Shum, Simon Buckingham. (2012). "Social learning analytics: five approaches". In *Proceedings of the 2nd International Conference on Learning Analytics and Knowledge* (LAK '12). https://doi.org/10.1145/2330601.2330616

Grandzol, C.J. and Grandzol, J.R., (2010). "Interaction in online courses: More is not always better", *Online Journal of Distance Learning Administration*, 13(2), 1-18.

Hayashi, R., Garcia, M., Maddawin, A., and Hewagamage, K.P., (2020). "Online learning in Sri Lanka's higher education institutions during the Covid-19 pandemic", *ADB Briefs No. 151*. Manila: ADB.

Lee, Kyungmee, Fanguy, Mik, Bligh, Brett and Lu, Xuefei Sophie, (2022). "Adoption of online teaching during the COVID-19 Pandemic: a systematic analysis of changes in university teaching activity", *Educational Review*, 74:3, 460-483, DOI: 10.1080/00131911.2021.1978401

Li, X, Lin, X, Zhang, F and Tian, Y., (2022) "What Matters in Online Education: Exploring the Impacts of Instructional Interactions on Learning Outcomes", *Front. Psychol*. 12:792464. doi: 10.3389/fpsyg.2021.792464

Macfadyen, L.P. and Dawson, S., (2010). "Mining LMS data to develop an "early warning system" for educators: A proof of concept", *Computers & education*, 54(2), 588-599.

Means, B. and Neisler, J., (2020). *Unmasking Inequality: STEM Course Experience During the COVID-19 Pandemic* [online], Digital Promise Global. Available from: https://files.eric.ed.gov/fulltext/ED614284.pdf [accessed 27 January, 2022]

Pagoto, S., Lewis, K.A., Groshon, L., Palmer, L., Waring, M.E., Workman, D., et al., (2021). "STEM undergraduates' perspectives of instructor and university responses to the COVID-19 pandemic in Spring 2020", *PLoS ONE*, 16(8): e0256213. https://doi.org/10.1371/journal.pone.0256213

Rapanta, C., Botturi, L., Goodyear, P., Guardia, L., and Koole, M., (2020). "Online University Teaching During and After the Covid-19 Crisis: refocusing teacher presence and learning activity", *Postdigital Science and Education*, 2: 923–945. https://doi.org/10.1007/s42438-020-00155-y

Ruipérez-Valiente, J.A., Muñoz-Merino, P.J., Delgado Kloos, C., (2018). "Improving the prediction of learning outcomes in educational platforms including higher level interaction indicators", *Expert Systems*, 35:e12298. https://doi.org/10.1111/exsy.12298

Ulfa, S. & Fatawi, I., (2021). "Predicting Factors that Influence Students' Learning Outcomes Using Learning Analytics in Online Learning Environment", *International Journal of Emerging Technologies in Learning*, 16(1), 4-17.

Vengroff, R. and Bourbeau, J., (2006). "In-class vs. on-line and hybrid class participation and outcomes: Teaching the introduction to comparative politics class", In *Proceedings of the Annual Meeting of the APSA Teaching and Learning Conference 2006*.

World Bank, (2020). COVID-19 Response – South Asia: Higher Education [online], World Bank. Available from: https://documents1.worldbank.org/curated/en/150411590701072157/COVID-19-Impact-on-Tertiary-Education-in-South-Asia.pdf [accessed 01 July, 2021]

Zacharis, N.Z., (2015). "A multivariate approach to predicting student outcomes in web-enabled blended learning courses", *The Internet and Higher Education*, 27, 44-53.