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Using Learning Analytics to Change Student Behaviour in the Global South

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ABSTRACT: *This study seeks to explore if student behaviour can be changed using social modelling, specifically to increase usage of a learning management system (LMS), and whether any such increased LMS usage leads to higher student grades. After years of research into learning analytics, exploring which indicator can best predict student performance, with hopes of using that insight to improve student outcomes, there remain very few empirical studies which are randomized controlled trials, which is necessary to identify causation, and none that take place in a blended learning environment in the Global South. As learning analytics is a subject area for improving the learning of students worldwide, it is time to include more than just the Global North. In this experiment, 309 first year undergraduate participants were randomly assigned to control and treatment groups. Each member in the treatment group was sent a weekly email containing a link to an online dashboard showing the student's performance compared against other students in the same cohort. Students in the treatment group did increase their use of the LMS but that increased usage did not translate into higher grades implying that the most important learning behaviours are not captured by the LMS, at least not in this study. Also of interest were that female students showed higher levels of engagement with the online dashboard and that the best predictor of a student's grade in the second half of the semester was the student's grade in the first half, supporting existing literature.*

KEYWORDS: learning analytics dashboard, learning management system, student outcomes, social modelling, global south.

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1. Introduction

For years, researchers have been studying the connection between learning analytics (LA) and student outcomes (Macfadyen & Dawson, 2010; Rafaeli & Ravid, 1997; Romero et al., 2013; Viberg et al., 2018). A natural focus of LA research efforts is on how LA can improve student outcomes, either through predicting which students need support, as a tool to guide educators which pedagogical choices are working to greatest effect, or even to change student behaviour.

Student behaviour was the first factor used to measure student engagement (Merwin, 1969), which is now widely accepted as key to student performance (Trowler & Trowler, 2010). Student behaviour, by itself, has been shown to predict student performance (Bloom, 1974). Therefore, it is reasonable to conclude that if a teacher can change the behaviour of a student then the teacher can improve that student's academic performance.

With the ubiquity of the internet, studying, which was once confined to the classroom, has moved to a blended format where students not only learn during class time but also independently through accessing online learning resources from a learning management system (LMS). Because an LMS allows student usage to be easily tracked (Andre et al., 2019), many researchers have been exploring how that data can be used to identify students at risk of dropping out (Hlosta et al., 2020), to more deeply understand the learning process (Viberg et al., 2018), and to predict student grades (Ifenthaler & Yau, 2020).

The next section will introduce several relevant background studies, then explain the research objective along with the methods used in the investigation. Findings will be discussed before conclusions are drawn and recommendations made.

2. Research background

2.1. Changing student behaviour

Many authors have identified that LMS usage data can be utilized to predict student grades (Conijn et al., 2017; Elbadrawy et al., 2015; Jo et al., 2015; Lu et al., 2018; Yang et al., 2017). Fewer researchers have explored whether LA interventions can act like nudges (Thaler & Sunstein, 2009) to change student behaviour in a way that is believed to positively impact learning outcomes (Hellings & Haelermans, 2020; Lim et al., 2019). However, those who have explored this have generally found that learners can be guided to change their behaviour.

An important question is whether the change in behaviour results in improved student outcomes. While some studies have found that a change in behaviour can improve student grades (Lim et al., 2019) others reported opposite findings (Hellings & Haelermans, 2020). In an earlier meta-analysis (Viberg et al., 2018), similar mixed findings were reported. It is important to note that all of these studies were conducted in the Global North.

When looking for which student behaviour to target for change, we need to identify which behaviour is most likely to impact student grades. While there are studies, mentioned above, that identify which LMS activity most strongly correlates with grades, other researchers have found that no LMS activity predicts future grades better than earlier grades (Conijn et al., 2017; Elbadrawy et al., 2015; Jayaprakash et al., 2014; Lu et al., 2018).

One challenge is that some studies in this area (Gong et al., 2018; Hu et al., 2014; Iglesias-Pradas et al., 2015) had very small sample sizes (fewer than 35 students). While these studies can introduce ideas for future investigation, we must be wary of drawing causal conclusions from them.

Another challenge is that very few studies were randomized controlled trials (RCTs). Of the three RCTs found which seek to use LA to improve student outcomes, only one reported that student behaviour was changed (Hellings & Haelermans, 2020). The other two (Dodge et al., 2015; Park & Jo, 2015) did not report either way. However, all three RCTs reported that student grades were unchanged as a result of the intervention. A fourth study (Lim et al., 2019), which was not an RCT, did find that student behaviour was changed and also that student grades improved. However, as there was no random assignment, there may be factors other than the intervention which created the change, although care was taken by the authors to address this concern.

2.2. Social cognitive theory

Social cognitive theory (Bandura, 2018) provides some insight on how to change student behaviour. The behaviourist concept of social modelling, a key part of social cognitive theory, says that by demonstrating behaviours to someone, it is possible to shape or change their behaviour. Since social modelling has been used to promote wide-scale changes in personal conduct (Bandura, 2007, p. 11), it is reasonable to believe it can be used in the field of education to guide students to change their behaviour toward learning. Indeed, using social modelling through the use of videos to change students' behaviour has been explored in multiple research studies (Devi et al., 2017).

2.3. Gender differences

Lim and colleagues (2019) explored the concept of gender in the context of LA but did not report any performance differences by gender. Jo and colleagues (2015) warned against exploring gender as a factor out of concern that if gender is found to be the most predictive of student grades, this could lead to the conclusion that interventions should be avoided because gender is not controllable. However, as the majority of business students in Vietnam are female, seeing what behavioural differences exist by gender may provide some useful insights.

2.4. Global South

The term Global North was devised to represent the countries of North America, Europe, Australia, Japan, etc. while the Global South represents the other countries. While most countries of the Global South are also in the geographical south, not all of them are. Global South countries, such as Vietnam, are often found to be former colonies of the Global North and, as such, face very different issues.

As the context of the Global South is often quite different from that of the Global North, it is important for research to be done which highlights the Global South so that any similarities or differences can be more clearly identified and we can begin to overcome the bias toward the Global North which exists in literature (Henrich, 2020). For example, in the Global North, it has been found that LMS usage drops as the semester progresses (Hellings & Haelermans, 2020; Lim et al., 2019). It would be useful to know if this pattern exists in the Global South as well.

Leitner (2019, p. 4) wrote that a challenge for LA research is “a shortage of studies empirically validating the impact” of learning analytics. This was further emphasized in a recent SoLAR webinar entitled “What Do We Mean by Rigour in Learning Analytics?” (Society for Learning Analytics Research, 2020).

In addition to the lack of rigorous studies, there is an absence of studies conducted in the context of blended learning in the Global South. The overwhelming majority of LA studies that have been done have taken place in the Global North, including all of the RCTs mentioned above.

As the Global South has very different challenges (such as much lower per capita GDP leading to lower funding levels for higher education), it is reasonable to expect that students, and the interventions which will be most impactful, might be different from what has been found in the Global North.

More randomized studies are clearly needed and they should include students from the Global South. An experiment to address this need is the focus of this paper and will be conducted using a mixed-methods approach.

2.5. Research objectives

The objective of this research is to explore to what extent presenting students with an LA dashboard, which compares the student’s LMS behaviour to that of their peers on a weekly basis, can increase the student’s interaction with the LMS and whether or not any such increase will lead to improved student grades.

3. Methods

The design of this experiment borrows heavily from social cognitive theory (Bandura, 2018) with the intent to change student behaviour. In short, this experiment used social modelling to help students to see how they can change their behaviour as a means of improving their performance. In the current study, the one doing the modelling (the one whose behaviour is being seen by the students under study), is being dynamically determined and is a peer rather than a teacher because the student is likely to feel more similar to their peer and, thus, more likely to copy the modelled behaviour.

A mixed-methods approach was taken whereby an initial quantitative study was performed and then, at the end of the study, three students, chosen from different grade-levels (top performing, low-performing, and middle), were interviewed to better understand the perspective of the students on the findings.

3.1. Sample

A total of 309 students studying two undergraduate business management courses, held at a large public university in Vietnam, were selected for the quantitative study. They comprised all students studying these two courses during this semester. Subjects were randomly assigned into treatment and control groups. With this selection technique, other factors that could impact the results are assigned to groups by chance which turns systematic error into random error (Mellenbergh, 2019) reducing the need to control for other factors.

Table 1. Participant data.

	Male	Female	Total
Treatment	64	91	155
Control	66	88	154
Total	130	179	309

All students were between 18 and 21 years old and in their first academic year at university. Most students had spent the previous year studying English intensively, as the program is an English-language program taught in a large Vietnamese public university.

3.2. Procedure

At the start of the semester, all students were notified that there would be an experiment and they would be divided into groups in the fourth week of the 13 week semester. They were all informed about the importance of both treatment and control groups and asked to respect these boundaries. They were all told that their behaviour in the experiment, including the completion of any questionnaires, would not impact their course grades in any way. They were also informed there would be a drawing at the end of the semester where approximately $87 (about 12 days average pay in Vietnam) would be awarded in a random drawing.

During week four, all students were asked to complete a series of questionnaires and were given two weeks to complete them. Up to three follow up emails were sent to students over the next two weeks to encourage them to finish the questionnaires.

Starting at the end of week six, all members of the treatment group received a weekly email which contained a link to an HTML report (see Appendix for a full sample report). Each section of the report contained data on how different categories of students behaved. As an example, Figure 1 is the first section:

Note: When it says "Top 10%" it means those students who have the best grades.

You logged into Moodle 2 times this past week. [how to improve]
- Top 10% average: 5 times
- Bottom 10% average: 1 times
- Rest of class average: 3 times

Show / hide chart

Figure 1. Report section 1.

In addition to the text, the user can show a chart of the data which will display the most recent five-week trend, as shown in Figure 2.

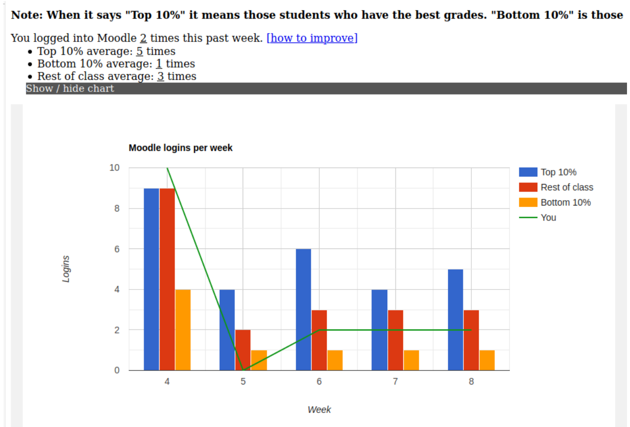


Figure 2. Report section 1 chart.

If the user clicked the "how to improve" link they were taken to a page explaining what is measured and how it might relate to their grade. An example of this can be seen in Figure 3.

How to Improve Moodle Login Count

Moodle does track when you login. So, to increase this count, you can simply login more often.

It is important to think about what this number really means. This number is a basic representation of how active you are on Moodle. Students with higher login counts are usually more active.

Having a higher login count is not the solution if you want higher grades or to learn more. The solution is to be more engaged and connected to the material on Moodle.

Moodle contains lots of articles and videos related to the subject you study. Are you reading and watching those?

Moodle also has grades and feedback. It also has discussion forums and quizzes to test your knowledge. Are you using those?

Those students who login more are more likely to use more resources.

So, the best thing to do is take advantage of the things your teacher has provided for you. If you do that you will naturally end up logging in more often.

Figure 3. Report section 1 improvement text.

The intention was to help students to see, both in textual data as well as graphically, how student LMS behaviour was linked to grades. For example, in Figure 2, it seems intuitively clear that more logins correlates with higher grades and fewer logins correlates with lower grades, even if the student does not understand exactly what correlation means.

The first nine sections were like this but for other indicators. Not all indicators were from the LMS. For example, lecture attendance was included in the report but was stored in a different system.

The 10th section had the student's grade by quartile. For example, a student might see "Your grade is currently in the top 25% of your class."

The final section was a bonus tip from learning science literature. An example is "Taking notes during class is known to improve learning. Additional benefits come from reviewing and editing your notes before you go to sleep the night of the lecture."

At the end of the semester, students were asked to complete another series of questionnaires.

4. Analysis

Since both the treatment and control groups were expected to interact with the LMS less in the second half of the semester, the measurement was the difference in the change of usage between the two groups. That is, was there or was there not a significant difference between the change in LMS usage of the treatment and control groups (differences in differences).

The intervention (weekly reports) began at the end of week six which is approximately half way through the semester. This allowed comparison of the usage in the first half (1H) to the usage in the second half (2H) of the term. The treatment group was compared to the control group using an independent samples t-test to see if any behavioural changes between the two groups were statistically significant.

Analysis was limited to the following LMS usage categories: 1) logins, 2) formative quiz attempts, 3) URL clicks, 4) file downloads, and 5) an aggregation (simple summation) of the these four measures as a proxy for overall interactivity with the LMS. Which members of the treatment group accessed their online weekly report and associated hints, including at what frequency, was also considered.

Finally, any relative increase in LMS usage by the treatment group correlating, using Person's r, with the average of 2H grades (there were six assessments before the start of the intervention and seven assessments after) was explored. The grade was evaluated as the percentage of the maximum grade available, to account for differing maximums for different assessments.

5. Findings and discussion

The following charts show the differences between the control (orange) and treatment (blue) groups. In all cases, we can see the treatment group declined less than the control group. In the case of URLs clicked, the treatment group actually increased slightly in 2H while the control group declined strongly.

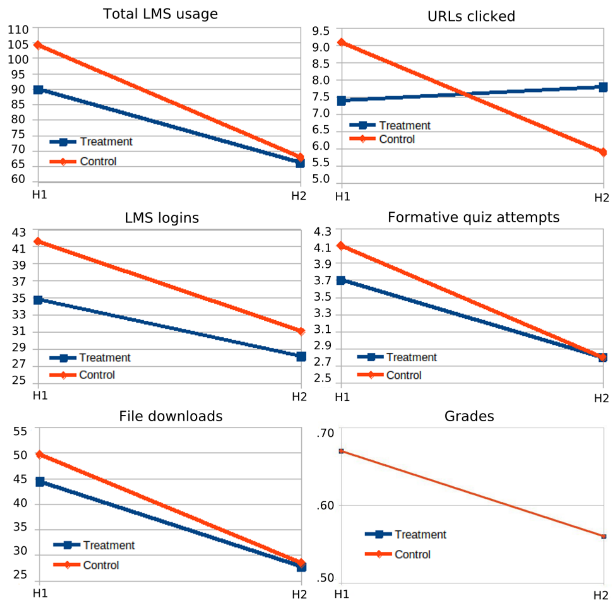


Figure 4. Charts comparing first and second half of semester.

It can be difficult to see in the chart of grades but the two lines overlap.

Comparing the means of the two groups involves

Table 2. Comparing Means

Measure	Control		Treatment		T-test signif.	Effect size Cohen's d
	Mean	SD	Mean	SD		
LMS usage	-36.18	39.31	-23.82	38.94	.01	.36
URL clicks	-3.14	12.31	0.38	12.85	.02	.28
File downloads	-21.26	25.86	-16.63	23.01	.10	.19
Quiz attempts	-1.28	1.47	-0.95	1.77	.08	.34
Logins	-10.50	14.09	-6.62	14.09	.02	.27

comparing the average change in behaviour. The numbers in Table 2 show the difference between 1H and 2H behaviour. Negative numbers show a decrease in activity in 2H. Only LMS usage, URL clicks, and LMS logins were statistically significant at the p = .05 level.

Comparing the differences of means, the data strongly indicates that this intervention can increase student LMS interactivity. That is, social modelling can be used to change student behaviour.

Cohen's d shows effect sizes between 0.19 and 0.36. Normally these ranges would be seen as a small to medium effect. However, it has been recommended to avoid using such standardized interpretations. An effect size of 0.36 might be considered small to medium but the question is whether or not that is an important level (Lipsey et al., 2012). To know that, we must compare the numbers to what is being found through other experiments in similar contexts. Unfortunately, with LA being a relatively new field, there are not many reports of Cohen's d. Therefore, we should consider the effect sizes of this intervention numerically but should reserve classifying them as low, medium, or high based on what future researchers find.

5.1. Correlations between change in LMS interactivity and grades

Looking at the correlations between the change in LMS use and 2H grades (Table 3), none of the LMS usage measures had a strong correlation (see column labelled "1") with 2H grades.

As shown in the chart of grades above, the treatment group did not have higher grades. In fact, the two groups averaged the exact same grade in both 1H and 2H.

The data strongly indicates that the increased LMS interactivity did not lead to correspondingly higher grades. This is in line with previous findings from the Global North (Hellings & Haelermans, 2020). This does not mean that changing student behaviour is not a worthy goal. The behaviour that should be targeted might be behaviour which is not captured by the LMS or simply was not explored in this investigation.

In Table 4 we can see the correlations of all variables of interest for 1H and 2H LMS usage.

As shown in column labelled "2" (2H grade), the item with the highest correlation is 2H logins (.516). However, that is still lower than 1H grade (.633, visible in the column labelled "1"). Confirming earlier literature, nothing in this study correlated better with grades than earlier grades. Although LMS logins, which strongly correlates (.860) with overall LMS usage, does give us a hint into which students will achieve higher grades.

One goal of this study was to identify if there was a causal link between higher LMS usage and higher grades. That is, if we can motivate students to use the LMS more, presumably they will be more engaged, will read more, will attempt more quizzes, and, as a result, will learn more and achieve a higher grade. All of the known LA experiments with random assignment, including this one, provide fairly clear evidence that this is not the case, at least any changes in performance are not visible in the near term.

Table 3. Correlations of Changes

Variable	1	2	3	4	5
(1) 2H grade					
(2) Δ Logins	-0.15				
(3) Δ File downloads	-.119*	.416**			
(4) Δ Quiz attempts	.025	.220**	.198**		
(5) Δ URL clicks	-.016	.196**	.311**	.156**	
(6) Δ LMS usage	-.083	.694**	.880**	.294**	.592**
* p < .05; ** p < .01					

Table 4 Correlations of variables of interest

Variable	1	2	3	4	5	6	7	8	9	10	11
(1) 1H grade	-										
(2) 2H grade	.663**										
(3) 1H logins	.345**	.427**	-								
(4) 2H logins	.369**	.516**	.775**	-							
(5) 1H downloads	.310**	.377**	.452**	.328**	-						
(6) 2H downloads	.262**	.426**	.364**	.474**	.647**	-					
(7) 1H quiz attempts	.412**	.455**	.474**	.404**	.417**	.408**	-				
(8) 2H quiz attempts	.300**	.456**	.424**	.481**	.342**	.478**	.692**	-			
(9) 1H URL clicks	.144*	.207**	.271**	.196**	.371**	.227**	.234**	.202**	-		
(10) 2H URL clicks	.133*	.124*	.136*	.233**	.145**	.358**	.218**	.318**	.288**	-	
(11) 1H LMS usage	.382**	.472**	.780**	.590**	.894**	.612**	.543**	.457**	.519**	.204**	-
(12) 2H LMS usage	.354**	.509**	.594**	.782**	.782**	.541**	.860**	.490**	.606**	.300**	.663**
* p < .05; ** p < .01											

5.2. Gender differences

If we explore the differences by gender, as suggested by Lim and colleagues (2019), even though no results were shown, we see that female students accessed their weekly reports much more often than their male classmates. Males accessed the hints more often but the number for both groups was extremely small, averaging less than one hint access over the entire six-week experiment.

Table 5. Report usage by gender

	Average accesses		Average grade	
	Report	Hint	1H	2H
Female	5.41	0.69	0.71	0.60
Male	3.72	0.89	0.61	0.50

The grades of women were consistently higher than the grades of men. Female students accessed their weekly report much more frequently (reports were only available in 2H) but the grades of women were consistently 10 percentage points above those of the men (in 1H and 2H). Therefore, there is no reason to believe that accessing the report more often leads to higher grades.

5.3. Temporal effect

Just as LMS usage went down as the semester progressed, confirming previous research (Hellings & Haelermans, 2020; Lim et al., 2019), so did LA report access. That is, LA report access was highest at the start of 2H but then slowly dropped over the remaining weeks.

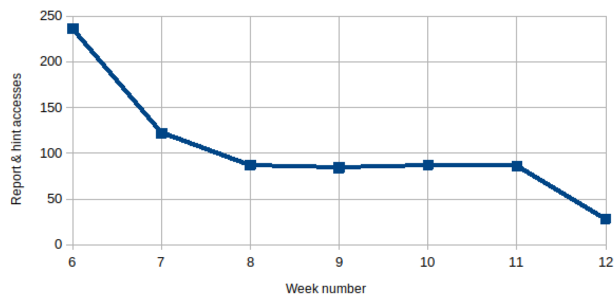


Figure 5. Report and hint access by week.

This drop in overall activity has two practical reasons, which were identified by post-experiment interviews with individual students. One student said:

"After three weeks or so, students figure out the pattern of how to perform well. Do not download slides before lecturers but pay close attention in the lecture. Pay close attention in the tutorials where the tutor explains how to do well in the

[assessed] workshops. Do what the tutor said in the workshops, get good grades."

A slightly different answer was given by another student when asked about the drop in LMS usage in the second half of the semester.

"Laziness and other courses having their assignments due so there is less time available. Maybe also problems with time management. Maybe just students are becoming less excited because it is no longer new."

First, students are more interested in "figuring things out" at the start of the course, when they feel greater confusion. As they gain more experience with a course, they feel less of a need to consume resources on the LMS. Second, 90% of other courses' assessments (for the students under investigation) were in the second half of the semester. That is, students' cognitive load increased from competing courses lowering the cognitive capacity available for any one course. This was supported by comments from a third student who said:

"The first half [of the semester] is too easy but the second half is too hard. Try to move the workload more to the start of the semester."

Given that students pay more attention to assessments and that 90% of other courses' assessments are in the second half of the semester, it is natural the students feel the second half is much more difficult.

What was unexpected was that URL clicks increased for the treatment group in the second half, implying the motivation from seeing the report was strong enough to overcome the cognitive burden from assessments in other subjects. It could also be that clicking extra links is a common reaction by students.

The file download category (of LMS usage data) included the syllabus, course text, assignment brief, workshop briefs, workshop schedules, lecture slides, and some articles. The strongest correlation of each of these items with 2H grades was the assignment brief (.424). Students who did not download the assignment brief might depend on those who did, indicating they are struggling more or are less engaged. Targeting students who do not download the assignment brief for additional support could be insightful.

5.4. Potential latent benefits

It is possible that important cognitive changes were made by the students but that those changes require more time to manifest in student behaviour. After all, these were first year undergraduate students and higher education is very different from the upper-secondary school experiences they are used to (in Vietnam). Therefore, it will be important to monitor these students for changes over time (see Ifenthaler & Yau, 2020). This could be done by exploring grades for these students as they progress through to graduation. However, without ongoing encouragement, it is possible that any treatment effects will wear off over time. Longitudinal LA experiments, as recommended by Ifenthaler and Yau (2020), would be useful here.

5.5. Subjective impact of experiment

At the end of the semester, students in the treatment group were asked what impact they felt the experiment had on their grades both in their current course as well as their other courses. Their answers can be seen in Figure 6.

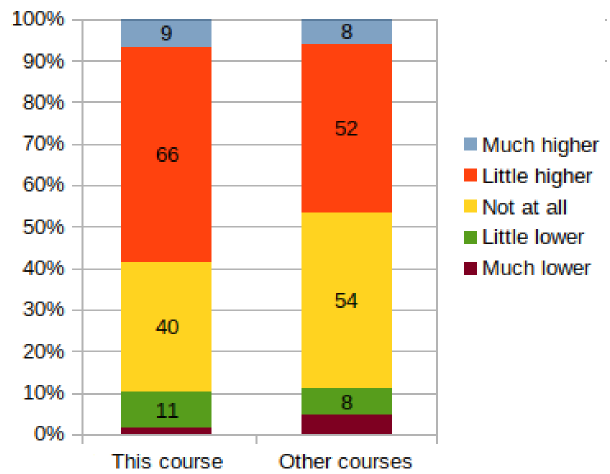


Figure 6. Subjective impact on grades.

Students in the treatment group felt like their grades went up not only in the current course but also in other courses. This implies that students felt they were learning things which could help them not just in their current subject but the other courses they study as well. As earlier research mentioned, sharing LMS usage data with learners can promote self-regulated learning (Lim et al.,

2019) and even meta-cognition (Webster et al., 2019). This finding provides further evidence of the possibility that changes were made by the student which might be seen over a longer period of time.

The vast majority (91%) of (treatment group) respondents reported that they found the weekly report useful.

When asked for more details on how the report was impacting the student, two common responses stood out as shown in Figure 7. The first was that the report made the students think about their learning. This meta-cognitive development is likely to have a long-term, rather than short-term, impact. The second was helping students to see the connection between behaviour and grades. There were 128 respondents to this question, with multiple choices possible by each.

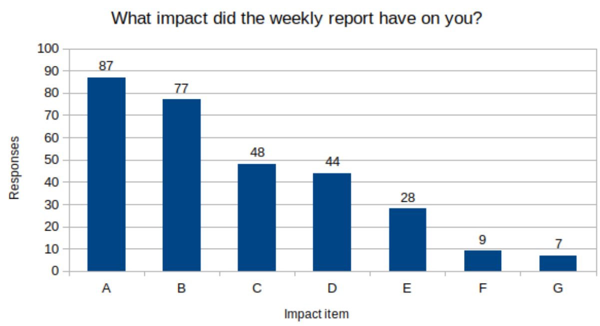


Figure 7. Number of students reporting changes due to report.

A) Made me think more about my learning

B) Helped me to see how my behaviour affected my learning and my grades

C) Kept me focused on my goals

D) Made me focus on learning

E) Made me worry about how much I am being tracked by Moodle

F) Made me think less about my learning

G) Made me want to trick the system by clicking more even though I did not read the materials

One of the dangers anticipated was students wanting to increase their reported numbers and doing so without the doing the underlying work (gaming the system). For example, they might just click all the URLs on the LMS without reading anything. The LMS is unable to determine what students read. It can only see if a link was clicked or not. However, only seven students (5%) reported engaging in such behaviour.

5.6. Student preference

When considering the various sections of the weekly report, the element students reported as being most useful was the bonus tip. The tip was different every week and came from learning science literature. The fact that students found that more interesting than any of the data implies that students may have some awareness of their own need for meta-cognitive development, as suggested by earlier research (Webster et al., 2019).

This finding is further supported by the fact that the most popular answer students gave to the question, “What impact did the weekly report have on you?” was to help them put more attention on their own learning process. This is the very definition of meta-cognition.

One of the students in the post-experiment interviews made a relevant comment here when she said:

I think the information on the report does not really impact my grade. I just read maybe half of the report and really just focused on the part of the report which showed my grade.

5.7. Identifying students in need of additional support

One of the promises of LA is to identify which students are in need of additional support before it is too late. This is why many papers have focused on answering the question, which LMS usage indicator can best predict future student grades (Conijn et al., 2017; Elbadrawy et al., 2015; Jo et al., 2015; Lu et al., 2018; Yang et al., 2017). However, at least in this research, LMS usage data was not as good a predictor of future student performance as earlier student grades. This matches earlier research (Conijn et al., 2017; Elbadrawy et al., 2015; Jayaprakash et al., 2014; Lu et al., 2018) and indicates that, if the goal is to identify students needing extra assistance, it might be better to add a greater number of assessments earlier in the semester.

This was also suggested by one of the students interviewed.

More smaller assessments are good because it gives visibility and students can figure out the pattern to success more quickly, before it is too late.

6. Conclusion

In this randomized experiment it has been found that through sending students weekly reports indicating the relationship between student behaviour (focusing on LMS activity) and student performance (grades), it is possible to get students to modify their behaviour. That is, educators can increase students' LMS usage by showing that LMS usage is positively correlated to grades. This makes sense intuitively as undergraduate students often confuse correlation and causation. However, there was no causal relationship between increased LMS usage and grades. That is, we can increase LMS usage because of the false cause fallacy (Manninen, 2018) but that does not translate into higher student grades. Since we know behaviour is key to student performance, this indicates that either LMS activity data does not capture the most important learning behaviour or did not capture it in this experiment.

When it comes to predicting student performance in the second half of the semester, the best predictor was the grade in the first half of the semester, in line with existing literature (Conijn et al., 2017; Elbadrawy et al., 2015; Jayaprakash et al., 2014; Jo et al., 2015; Lu et al., 2018).

Interestingly, females (in the treatment group) accessed their weekly report an average of 5.4 times while men did so only 3.7 times. Females also achieved higher grades. However, the difference in grades (about 10 percentage points) was consistent from H1 to H2. This is further evidence that increased interactivity with LA systems does not improve student outcomes.

All of this does not mean LA has no potential value. There are still countless ways that LA can be used to help students, for example using LA to teach students about data analytics and data-based decision-making (particularly useful for business students who were the subjects of this investigation), to identify students who are not engaging with the materials, or to use these weekly prompts to improve student meta-cognition. Some of these options will be listed in the following section on future research.

7. Limitations

This study has its limitations, including a relatively small sample size. While participants were randomly assigned to their groups, there were only 309 students. Before depending on the conclusions drawn herein, this study should be replicated, especially in different cultures, although this study's findings are in line with research from the Global North.

It has been suggested that when LMS usage does not correlate strongly with student grades, that may indicate an issue with the materials on the LMS (Elbadrawy et al., 2015). That is, the URLs and resources included in these courses might not be supporting students getting higher grades. If these materials were different, the results might also be different.

This study also provided feedback to students only once per week. It is possible that if there were more frequent reports to students this might have increased LMS usage more strongly, breaking above some hypothetical usage threshold which could have changed the impact on learning and grades.

8. Implications and recommendations

Since LMS usage data does not provide a better predictor of student performance than previous student performance, rather than using learning analytics to indicate which students are in the greatest need of additional support, it would be better to introduce a greater number of assessments throughout the semester. That is, a greater number of low-stakes assessments could give visibility to both educators and students into who needs extra attention.

In other research (Zimmerman & Johnson, 2017) (n=353) which did not use an LMS, it was shown that an early quiz (in the second week) was a good predictor of who will complete a statistics course and who will not.

Additionally, in the post-experiment interviews, having multiple assessments was mentioned as something which gave students greater understanding of whether or not they were on the right path.

Previous research, this experiment, and student interviews all indicate that having more assessments in a course, especially starting early, can bring important benefits.

9. Further research

As mentioned in the conclusion, while this study indicates that simply informing students of the connection between student LMS activity and student grades was not enough to improve student performance, there is still much potential in LA research. In this section, we explore some of these areas.

Data analytics has become a very important area in all aspects of business (customer analytics, talent analytics, etc.). Using LA to help students to better realize how data analytics can be applied by having their own usage reported may help them understand more deeply about this topic.

Since women in the treatment group accessed their reports more than men, we should explore if this means male higher education students are less engaged and, if so, whether this is a cultural issue limited to this context. Using LA as a way to improve student engagement, with the materials as opposed to only measurable elements, could be a better path to improving student performance. For example, by seeing which elements are being underutilized by male students, the teacher can address in the lecture why males might find these other materials interesting as well.

Using weekly emails to not just report usage data to students but also trigger structured reflection could offer a way to improve meta-cognition with no additional effort from the teacher. For example, simply by adding a sentence at the start of the weekly email reminding students to consider how the data in this report might help them change their behaviour, students might improve their meta-cognitive abilities on their own.

As this experiment has led to additional questions, perhaps one of the key benefits is to use LA as a way to gain insight into questions for education researchers to explore. That is, focusing LA efforts on research analytics. As one example, why do female students seem more engaged than their male classmates?

As has been mentioned by others (Ifenthaler & Yau, 2020), large-scale longitudinal studies could be very helpful, especially in seeing if there are changes made which simply take longer than one semester to manifest in observable behaviour. Future follow up will be scheduled with the students in this current study to see if any measurable changes can be seen after a year or two.

Finally, using LA to promote student meta-cognition, agency, or other aspects of student psychology could lead to lasting, long-term effects. Such studies would likely need to be longitudinal in nature but could be among the most powerful uses of LA. This is supported by student responses to this experiment where they mentioned the most useful aspect of their weekly report was the bonus tip based on learning science literature.

References

Andre, J., Le, T. K., & Webster, R. (2019). Academic Leadership and Learning Analytics in Higher Education in Vietnam. *Leadership and Management in Higher Education: Driving Change with Global Trends*, 16.

Bandura, A. (2007). Reflections on an Agentic Theory of Human Behavior. *Journal of the Norwegian Psychological Association, 44*(8).

Bandura, A. (2018). Toward a Psychology of Human Agency: Pathways and Reflections. *Perspectives on Psychological Science, 13*(2), 130–136. https://doi.org/10.1177/1745691617699280

Bloom, B. S. (1974). Time and learning. *American Psychologist, 29*(9), 682.

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

Devi, B., Khandelwal, D. B., & Das, M. (2017).

Application of Bandura's social cognitive theory in the technology enhanced, blended learning environment. *International Journal of Applied Research, 3*(1), 721–724.

Dodge, B., Whitmer, J., & Frazee, J. P. (2015). Improving undergraduate student achievement in large blended courses through data-driven interventions. *Proceedings of the Fifth International Conference on Learning Analytics And Knowledge - LAK '15*, 412–413. https://doi.org/10.1145/2723576.2723657

Elbadrawy, A., Studham, R. S., & Karypis, G. (2015). Collaborative multi-regression models for predicting students' performance in course activities. *Proceedings of the Fifth International Conference on Learning Analytics And Knowledge*, 103–107. https://doi.org/10.1145/2723576.2723590

Gong, L., Liu, Y., & Zhao, W. (2018). *Using Learning Analytics to Promote Student Engagement and Achievement in Blended Learning: An Empirical Study*. 6.

Hellings, J., & Haelermans, C. (2020). The effect of providing learning analytics on student behaviour and performance in programming: A randomised controlled experiment. *Higher Education*. https://doi.org/10.1007/s10734-020-00560-z

Henrich, J. (2020). *The WEIRDest People in the World: How the West Became Psychologically Peculiar and Particularly Prosperous (Illustrated edition)*. Farrar, Straus and Giroux.

Hlosta, M., Papathoma, T., & Herodotou, C. (2020). Explaining Errors in Predictions of At-Risk Students in Distance Learning Education. In *I. I. Bittencourt, M. Cukurova, K. Muldner, R. Luckin, & E. Millán (Eds.), Artificial Intelligence in Education (Vol. 12164, pp. 119–123)*. Springer International Publishing. https://doi.org/10.1007/978-3-030-52240-7_22

Hu, Y.-H., Lo, C.-L., & Shih, S.-P. (2014). Developing early warning systems to predict students' online learning performance. *Computers in Human Behavior, 36*, 469–478. https://doi.org/10.1016/j.chb.2014.04.002

Ifenthaler, D., & Yau, J. (2020). Utilising learning analytics to support study success in higher education: A systematic review. *Educational Technology Research and Development, 2020(June)*. https://doi.org/10.1007/s11423-020-09788-z

Iglesias-Pradas, S., Ruiz-de-Azcárate, C., & Agudo-Peregrina, Á. F. (2015). Assessing the suitability of student interactions from Moodle data logs as predictors of cross-curricular competencies. *Computers in Human Behavior, 47*, 81–89. https://doi.org/10.1016/j.chb.2014.09.065

Jayaprakash, S. M., Moody, E. W., Lauría, E. J. M., Regan, J. R., & Baron, J. D. (2014). Early Alert of Academically At-Risk Students: An Open Source Analytics Initiative. *Journal of Learning Analytics, 1*(1), 6–47. https://doi.org/10.18608/jla.2014.11.3

Jo, I.-H., Yu, T., Lee, H., & Kim, Y. (2015). Relations between Student Online Learning Behavior and Academic Achievement in Higher Education: A Learning Analytics Approach. In G. Chen, V. Kumar, Kinshuk, R. Huang, & S. C. Kong (Eds.), *Emerging Issues in Smart Learning (pp. 275–287*). Springer Berlin Heidelberg. https://doi.org/10.1007/978-3-662-44188-6_38

Leitner, P., Ebner, M., & Ebner, M. (2019). Learning Analytics Challenges to Overcome in Higher Education Institutions. In D. Ifenthaler, D.-K. Mah, & J. Y.-K. Yau (Eds.), *Utilizing Learning Analytics to Support Study Success (pp. 91–104)*. Springer International Publishing. https://doi.org/10.1007/978-3-319-64792-0_6

Lim, L.-A., Gentili, S., Pardo, A., Kovanović, V., Whitelock-Wainwright, A., Gašević, D., & Dawson, S. (2019). What changes, and for whom? A study of the impact of learning analytics-based process feedback in a large course. *Learning and Instruction, 10*1202. https://doi.org/10.1016/j.learninstruc.2019.04.003

Lipsey, M. W., Puzio, K., Yun, C., Herbert, M. A., Steinka-Fry, K., Cole, M. W., Roberts, M., Anthony, K. S., & Busick, M. D. (2012). Translating the Statistical Representation of the Effects of Education Interventions Into More Readily Interpretable Forms. *Institute of Education Sciences*.

Lu, O. H. T., Huang, A. Y. Q., Huang, J. C. H., Lin, A. J. Q., & Yang, S. J. H. (2018). Applying Learning Analytics for the Early Prediction of Students' Academic Performance in Blended Learning. *Educational Technology & Society, 21*(2).

Macfadyen, L. P., & Dawson, S. (2010). Mining LMS data to develop an "early warning system" for educators: A proof of concept. *Computers & Education, 54*(2), 588–599. https://doi.org/10.1016/j.compedu.2009.09.008

Manninen, B. (2018). False Cause: 100 of the Most Important Fallacies in Western Philosophy (pp. 338–341). https://doi.org/10.1002/9781119165811.ch79

Mellenbergh, G. (2019). Random Assignment (pp. 39–54). https://doi.org/10.1007/978-3-030-12272-0_4

Merwin, J. C. (1969). Historical review of changing concepts of evaluation. In Educational evaluation: New roles, new methods: The sixty-eighth yearbook of the National Society for the Study of Education, Part II. University of Chicago Press.

Park, Y., & Jo, I.-H. (2015). Development of the Learning Analytics Dashboard to Support Students' Learning Performance. *Journal of Universal Computer Science, 21*(1).

Rafaeli, S., & Ravid, G. (1997). OnLine, Web Based Learning Environment for an Information Systems course: Access logs, Linearity and Performance. ISECON 97. *Information Systems Education Conference*.

Romero, C., López, M.-I., Luna, J.-M., & Ventura, S. (2013). Predicting students' final performance from participation in on-line discussion forums. *Computers*

& *Education, 68*, 458–472. https://doi.org/10.1016/j.compedu.2013.06.009

Society for Learning Analytics Research. (2020, November 13). [Webinar] What Do We Mean by Rigour in Learning Analytics? https://www.youtube.com/watch?v=RxGa6MvCX6Y&feature=youtu.be

Thaler, R. H., & Sunstein, C. R. (2009). Nudge: Improving Decisions About Health, Wealth, and Happiness.

Trowler, P., & Trowler, V. (2010). Student engagement evidence summary. *The Higher Education Academy.*

Viberg, O., Hatakka, M., Bälter, O., & Mavroudi, A. (2018). The current landscape of learning analytics in higher education. *Computers in Human Behavior, 89*, 98–110. https://doi.org/10.1016/j.chb.2018.07.027

Webster, R., Andre, J., & Trinh, T. T. G. (2019). Industry 4.0 and higher education: Combining learning analytics and learning science to transform the undergraduate learning experience in Vietnam. Leadership and Management in Higher Education: Driving Change with Global Trends. *Leadership and Management in Higher Education: Driving Change with Global Trends*, Ho Chi Minh City.

Yang, T.-Y., Brinton, C. G., Joe-Wong, C., & Chiang, M. (2017). Behavior-Based Grade Prediction for MOOCs via Time Series Neural Networks. *IEEE Journal of Selected Topics in Signal Processing, 1–1*. https://doi.org/10.1109/JSTSP.2017.2700227

Zimmerman, W. A., & Johnson, G. (2017). Exploring Factors Related to Completion of an Online Undergraduate-Level Introductory Statistics Course. *Online Learning, 21*(3). https://doi.org/10.24059/olj.v21i3.1017

Appendix – Sample Report

Report for Suzi Student

ID 12345678

Week 9

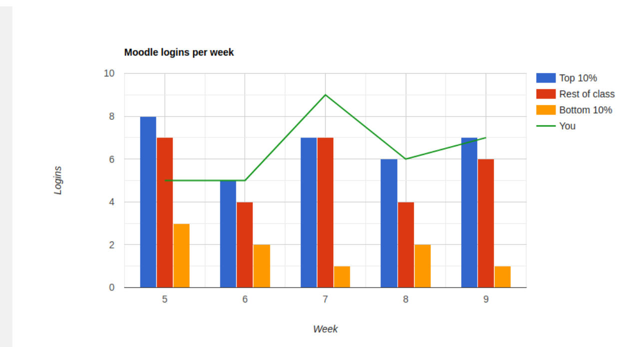
Assessment(s) WS04-D (Workshop) and WS04-Peer (Peer evaluation)

This report will show you how your behavior is similar to, or different from, various groups of students. Try to look for patterns in the data and see how you can improve your grade by changing your behavior.

Note: When it says "Top 10%" it means those students who have the best grades. "Bottom 10%" is those students who have the worst grades.

You logged into Moodle 7 times this past week. [how to improve]
- Top 10% average: 7 times
- Bottom 10% average: 1 times
- Rest of class average: 6 times

Show / hide chart



You accessed 38% of available resources about this week's topic. [how to improve]
- Top 10% averaged: 39%
- Bottom 10% averaged: 15%
- Rest of class averaged: 26%

Show / hide chart

You accessed 65% of available resources so far (for this week and all previous weeks). [how to improve]
- Top 10% averaged: 42%
- Bottom 10% averaged: 25%
- Rest of class averaged: 37%

Show / hide chart

You did complete the most recent formative quiz. [how to improve]
- Top 10%: 82% completed it
- Bottom 10%: 10% completed it
- Rest of class: 38% completed it

Show / hide chart

You did download the slides before the most recent lecture. [how to improve]
- Top 10%: 27% downloaded it
- Bottom 10%: 0% downloaded it
- Rest of class: 11% downloaded it

Show / hide chart

You did review your feedback online this week. [how to improve]
- Top 10%: 45% reviewed it this week
- Bottom 10%: 10% reviewed it this week
- Rest of class: 49% reviewed it this week

Show / hide chart

You looked at 0 discussions in the forums this week. [how to improve]
- Top 10% averaged: 3 views
- Bottom 10% averaged: 0 views
- Rest of class averaged: 1 views

Show / hide chart

You posted 0 times in the forums this week. [how to improve]
- Top 10%: 0% posted something this week
- Bottom 10%: 0% posted something this week
- Rest of class: 1% posted something this week

Show / hide chart

You did attend the most recent lecture. [how to improve]
- Top 10%: 82% attended the lecture
- Bottom 10%: 30% attended the lecture
- Rest of class: 90% attended the lecture

Show / hide chart

Your grade for the last assessment was 40 (out of 50) for the Workshop; 5 (out of 15) for the Peer evaluation. Is that good enough to meet your goals? [how to improve]
- Top 10% average: 43 for the Workshop; 14 for the Peer evaluation
- Bottom 10% average: 3 for the Workshop; 1 for the Peer evaluation
- Rest of class average: 25 for the Workshop; 10 for the Peer evaluation

Show / hide chart

Your grade is currently in the top 25% of your class

Show / hide chart

Did you review your ASSIST profile (with the ASSIST Interpretation doc) trying to understand yourself better? Doing this every week will help you.

What do you plan to change for next week? It helps if you write it down on paper and review it every week.

Bonus tip: Each study time should have a specific goal. Before you start studying, set a study session goal that supports your overall academic goal (for example, Read and summarize one journal article on talent management.)