Linking students' timing of engagement to learning design and academic performance

Conference or Workshop Item

Linking Students' Timing of Engagement to Learning Design and Academic Performance

Quan Nguyen
Open University UK
Institute of Educational Technology
United Kingdom
quan.nguyen@open.ac.uk

Michal Huptych
Open University UK
Knowledge Media Institute
United Kingdom
michal.huptych@open.ac.uk

Bart Rienties
Open University UK
Institute of Educational Technology
United Kingdom
bart.rienties@open.ac.uk

ABSTRACT

In recent years, the connection between Learning Design (LD) and Learning Analytics (LA) has been emphasized by many scholars as it could enhance our interpretation of LA findings and translate them to meaningful interventions. Together with numerous conceptual studies, a gradual accumulation of empirical evidence has indicated a strong connection between how instructors design for learning and student behaviour. Nonetheless, students' timing of engagement and its relation to LD and academic performance have received limited attention. Therefore, this study investigates to what extent students' timing of engagement aligned with instructor learning design, and how engagement varied across different levels of performance. The analysis was conducted over 28 weeks using trace data, on 387 students, and replicated over two semesters in 2015 and 2016. Our findings revealed a mismatch between how instructors designed for learning and how students studied in reality. In most weeks, students spent less time studying the assigned materials on the VLE compared to the number of hours recommended by instructors. The timing of engagement also varied, from in advance to catching up patterns. High-performing students spent more time studying in advance, while low-performing students spent a higher proportion of their time on catching-up activities. This study reinforced the importance of pedagogical context to transform analytics into actionable insights.

CCS CONCEPTS

• Applied computing~Distance learning • Applied computing~E-learning • *Applied computing~Computer-assisted instruction*

KEYWORDS

Learning Analytics, Learning Design, Virtual Learning Environment, Higher Education, Temporal, Engagement.

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INTRODUCTION

Recent years have witnessed an increased interest to leverage Learning Analytics (LA) to inform and support Learning Design (LD) [22, 25, 30]. One of the main benefits of aligning LA with LD is that LA could act as a reflective resource on how students actually behave compared to instructors' assumptions embedded in their LD, which has been echoed by many scholars [10, 25]. Although substantial progress has been made within the LAK community to link how instructors' LD decisions with what students are doing [1, 22, 27, 32, 33], one major methodological challenge that is often ignored is the synchronization of the concept of time between LD and LA. Most LD activities are conceptualized at a weekly level, or even at a course level. However, the actual behaviour of students occurs on a much finer, hours per hour or even second by second level. It is inevitable that this will lead to discrepancies between intended and actual observed learning behaviours. In other words, there remains a paucity of empirical evidence on the magnitude and temporal characteristics of behavioural differences in online environments, and how differences in behavioural patterns of students might vary across different levels of academic performance.

1.1 Background

Learning Design, or "Design for Learning"[13], is an emerging field since the early 2000s, which aims at developing a descriptive framework to capture teaching, and learning activities so that teaching ideas can be shared and reused from one educator to another [7, 10, 20, 24]. By explicitly representing the learning activities designed for students, educators are enabled to reflect on their learning designs and identify potential issues. For instance, in a study of 148 LDs by Toetenel and Rienties [37], the introduction of visualizations of initial LDs accompanied by interactive workshops helped educators to focus on the development of a range of pedagogical and technological skills, and more importantly relatively better "balanced" LDs.

Besides reflecting on the LD itself, another important source of feedback is generated from students, their profiles, behaviour and cognition. In an interview-based study of 30 instructors, Bennett, Agostinho and Lockyer [3] identified student-related factors (e.g., cohort profile, learning objectives, feedback from past sessions) as one of the key factors (together with instructors-related factors and context-related factors) that influenced how instructors engaged in the design process.

While feedback from students is vital for the improvement of LD, there are several challenges in terms of the types of feedback and how they are gathered. A first challenge lays in the timing of the feedback, which often takes place after the learning process has finished (e.g., satisfaction survey at end of the module, final exams) [19, 26]. Not only may these kinds of feedback be subject to self-report bias and sampling bias, they also prevent educators from making in-time interventions as these forms of data are mostly collected at the end of a module. A second challenge is the quality of feedback. Direct interactions with students during class could give important verbal and non-verbal cues of how students react to a certain LD [4, 6]. However, in blended and online environments reacting to feedback from individual students might be restricted. One potential way forward is to harvest the digital footprints of students in Virtual Learning Environments (VLEs) as proxies of how they engage in learning activities, so-called LA [11].

The field of LA has experienced a substantial growth in the last six years since the first LAK conference in Banff, Canada. Among a wide variety of topics in LA, the alignment between LA and LD has attracted substantial interest [1, 21, 27, 32]. First, the analysis of trace data could equip educators with authentic and fine-grained proxies of how students engage in online learning activities. Second, by capturing and visualizing the design of learning activities, the LD approach could provide a pedagogical context to support interpreting and translating LA findings into interventions [22, 30]. A gradual accumulation of empirical evidence has indicated great potential of connecting LA with LD [12, 27-29, 32, 33]. For example, in a large-scale study of 151 modules and their 111,256 students at a distance educational institution, Rienties and Toetenel [33] revealed significant relations between LD and VLE behaviour, along with student satisfaction, and retention. The findings showed that taking the context of LD into account could increase the predictive power of student behaviour by 10-20%. Recently, a longitudinal study of 38 modules by Nguyen, Rienties, Toetenel, Ferguson and Whitelock [29] indicated that by controlling for the heterogeneity between modules and time periods, LD could explain up to 69% of the variance in the time spent on VLE. In addition, Rodríguez-Triana, Martínez-Monés, Asensio-Pérez and Dimitriadis [34] illustrated the potential of orchestrating a monitoring-aware design process, and scripting-aware monitoring process to support instructors to design computer-supported collaborative learning activities. The consideration of instructional condition is crucial for the development of LA, as it could prevent over- or underestimation of the effect of behaviour in VLE on performance [12]. Visualizations of students activities or predictive model of at-risk students could offer insights to instructors and instructional designers, but not actionable unless the analytics is linked with LD [36].

When instructors design for learning, they often estimate the workload of each activity and the corresponding time period for each activity (e.g. take 3 hours to read chapter 2 in week 2). LD is often embedded in the course syllabus, and acts as a guideline for students to self-regulate their learning process [4, 9, 39]. However, learners as agents consciously and perhaps opportunistically make decisions on what, how, and when to engage in a particular range of learning activities [41]. While instructors might think that a student will read chapter 2 in week 2, perhaps some students are already pre-reading materials from week 4, while other students may not have watched the introduction video of week 1. Therefore, by having a better understanding of how much time students spent on respective learning materials and, more importantly for this study, when in time they studied these learning materials, this may enhance our intertemporal understanding of how students make complex study decisions.

While previous research has shown a strong correlation between the LD and student behaviour on VLE [27, 29, 33], the collapse of the time spent on all activities under a module or a week remains a problem for interpretation. For example, not all activities on the VLE are relevant and comparable to the LD (e.g. personal site, library service, accessibility service). Secondly, the timing of studying has not been fully understood (i.e., studying all materials of week 2 on day 8, 9, or 13). For instance, students could study the learning materials before or after the assigned week. Therefore, this study takes a further step to investigate the time spent on each individual activity and when the students engage in these activities.

RQ1: To what extent do students' timing of engagement align with the instructors' learning design?

Furthermore, many LA studies have indicated that trace behaviours are significantly related to their academic performance [23, 35]. In addition, extensive research has shown that the ability to plan study time and tasks (time management) was found to be a significant predictor of academic performance [5, 14]. It has been widely acknowledged that students with better learning strategies and self-regulation strategies are more on track with managing their study choices, while students who end up behind the course schedule might struggle to effectively perform over time [15, 40]. Thus, we hypothesize that high-performing students spend more time studying the learning materials in advance, or in line with the learning design, while low-performing LD students spend more time in catching up in their study.

RQ2: How do different levels of performance and learning design relate to different study patterns?

2 METHOD

2.1 Setting and participants

This study took place at a public distance education institution in the UK, namely the Open University UK (OU). The context of the study is a level 2 module, 30 credits, which corresponds to the 2nd-year course at normal face-2-face universities, focusing on Environmental Studies. Given our research questions, which focused on comparing instructors' assumptions and actual student behaviour, it is crucial to ensure an accurate representation of the actual learning activities. Therefore, this module was selected because the majority of its learning activities took place on the VLE, in this case, a Moodle platform. This allowed us to capture a more reliable representation of actual online learning behaviour compared to other modules at the OU, whereby learning activities could take place outside of the VLE (e.g., reading PDFs, printed materials, blended learning) [38].

There were 268 and 267 registered students in Fall 2015 and Fall 2016 respectively. However, since our research questions focus on exploring the study patterns across different groups of performance (based on final scores), the analysis in this study only took into account the students who completed the course. Thus, the analysis was conducted on 182 and 198 students in Fall 2015 and Fall 2016 respectively. In the 2015 implementation, there were more male (61.58%) than female students. The majority of the students were from the UK (91.84%) and of white ethnicity (88.68%). In contrast with typical university student profiles, only 13.95% of the students were under 25 years old, while 44.21% were from 26 to 35, 26.84% from 36 to 45, 10.26% were from 46 to 55, and 4.74% were over 56. Most students had a full-time job (63.68%), or part-time job (15.79%) while taking the course. The prior educational qualification of students in this module was also diverse, with 28.95% less than A levels, 38.95% with A-levels or equivalent, and 28.42% with a higher education qualification. The demographics figures stayed consistently in the 2016 implementation.

2.2 Learning Design

The first dataset which captured the respective module LD was a result of an institutional-wide initiative, which helps teams in defining their pedagogic approach, choosing and integrating an effective range of media and technologies, and enable sharing of good practice across the university [8]. In order to classify learning activities in an objective and consistent manner, a mapping process was created. In particular, each module goes through a mapping process by a module team which consists of a LD specialist, a LD manager, and faculty members. First, the learning outcomes specified by the module team were captured by a LD specialist. Each learning activity within the module's weeks, topics, or blocks was categorized under the LD taxonomy (Table 1) and stored in an 'activity planner' – a planning and design tool supporting the development, analysis, and sharing of learning designs. Next, the LD team manager reviews the resulting module map before the findings are forwarded to the faculty. This provides academics with an opportunity to comment on the data before the status of the design was finalized. This process typically takes between 1 and 3 days for a single module, depending on the number of credits, structure, and quantity of learning resources.

The seven types of learning activity were measured in terms of the duration (in hours) that was recommended for each type of activity in a particular week. The number of credits to be gained determined the total workload of each module, which is the sum of the time allocated for all seven types of learning activity. Generally speaking, each credit is associated with 10 hours of study (so 30 credits = 300 h and 60 credits = 600 h). However, the actual workload can be different and depends on each module's implementation, student characteristics, and student abilities.

Table 1: Learning design taxonomy

	Type of activity	Example
Assimilative	Attending to information	Read, Watch, Listen, Think about, Access.
Finding and handling information	Searching for and processing information	List, Analyse, Collate, Plot, Find, Discover, Access, Use, Gather.
Communication	Discussing module related content with at least one other person (student or tutor)	Communicate, Debate, Discuss, Argue, Share, Report, Collaborate, Present, Describe.
Productive	Actively constructing an artefact	Create, Build, Make, Design, Construct, Contribute, Complete,
Experiential	Applying learning in a real-world setting	Practice, Apply, Mimic, Experience, Explore, Investigate.
Interactive /adaptive	Applying learning in a simulated setting	Explore, Experiment, Trial, Improve, Model, Simulate.
Assessment	All forms of assessment (summative, formative and self-assessment)	Write, Present, Report, Demonstrate, Critique.

Source: Retrieved from Rienties and Toetenel [33]

In our target module, there are five different types of learning activities, whereby three types of activities (assimilative, productive, assessment) accounted for 91.64% of the total workload, which were included for comparison purposes. This was due to the difficulty in capturing the actual time spent on finding and handling activities since students could go outside of the VLE for searching information [16]. At the same time, measuring time spent on communication was troublesome, as the compulsory communication activities designed to support certain tasks, and the optional communication activities (e.g., social, café talk) were collapsed under one discussion forum. On average, students in this module were expected to spend 7 hours each week for assimilative, productive, and assessment activities combined. Assimilative activities were allocated on average 4.05 hours per week (SD=3.32), followed by productive activities (M=1.47, SD=1.24), and assessment activities (M=1.49, SD=2.88). Even though the learning designs remained almost the same between the two semesters, there were two small changes. In particular, there were only two tutor-marked assignments (TMAs) in 2016 instead of three assignments in 2015. Study materials of week 12 and 13 were combined in 2015, while they were separated for each week in 2016.

2.3 VLE engagement

The second dataset consisted of clickstream data of individual learners from the VLE and was retrieved using SAS Enterprise 9.4. The data were captured from four weeks before the start of the module until four weeks after the end of the module. Learning activities were planned over 30 weeks. Data were gathered in two semesters (Fall 2015 and Fall 2016) in order to validate the findings from two independent implementations. First, we would like to mention that the student behaviour record includes all students' VLE activity. In other words, "the spent time" is determined as the time between any two clicks of a student, regardless a course and a type of the VLE activity. Further, not each click can be associated with studying time; for instance, there are clicks related to downloading of some material. We have this information about an action type which is connected with the click. Thus, we can determinate that a click with the connected action "download" was not included in the spent time of student in the analysis. Nonetheless, we can assume that the time of a click with the connected action "view" is associated with the time of learning of a study material for which the click is logged.

To compare the LD with the actual student behaviour, time spent on task was calculated as the duration between clicks. As pointed out by previous research [17], this metric could be problematic due to (1) the inability to differentiate between active time and non-active time (students leave the respective web page open and go for a coffee), and (2) the last click of the day is followed by a click next day), which makes the duration excessively long. Any attempt to set an arbitrary cut-off value would pose a threat in underestimating or overestimating of the actual engagement time.

Taking into account the context and LD of a module could produce a more informed cut-off value. Ideally, this cutoff value should be tailored to the design and context of each individual activity. For example, the cut-off value should be different between a 20 minutes activity and a 1-hour activity. While this study does not fully address the aforementioned problems, it leveraged the design of learning activities (discussion between researchers and designers) to set a cut-off value at 1 hour for all activity (e.g. any activity goes beyond 1 hour will be set as 1 hour).

Since our research question aims at examining to what extent students' timing of engagement aligns with instructor learning design, two types of study patterns were computed which capture how much time a student spent on studying a particular study material:

(1) in advance – material x assigned to week t was studied during or before week t

(2) catching up and revise – material x assigned to week t was studied after week t.

In the second research question, we are interested in understanding how these two patterns of learning behaviours varied across three different groups of performance, which was measured as the average of all tutor-marked assignments (TMAs) and final exams:

- Failed (average score < 40% or final exam score < 40%),
- Passed (40% < average score < 75% and final exam score >= 40%), and
- Excellent (average score > 75% and final exam score >= 40%).

This categorization builds on previous predictive analytics research [18], which estimated these three categorizations of students across large numbers of students. Of all students completed who the course, there were 52 failed students (M=21.2 %, SD=16.7 %), 106 passed students (M=63.6 %, SD=7.5 %), and 31 excellent students (M=79.5 %, SD=3.7%) in 2015, and 50 failed students (M=25.4 % SD=15.9), 119 passed students (M=63.1 %, SD=8.0 %), and 29 excellent students (M=79.7 %, SD=3.2 %) in 2016.

2.4 Data Analysis

2.4.1 Visualizations. To address our first research question, we visualized actual study patterns against the LD over 30 weeks. Second, we visualized the study patterns for respective individual study materials across excellent, passed, and failed group. The visualizations were done using Jupyter Notebook and Tableau.

2.4.2 Multilevel modelling. In order to compare study patterns across three groups of performance over time, we used a multilevel modelling (MLM) (or mixed-effect modelling) approach (week t is nested within student i). Compared to the traditional repeated measure ANOVA approach, MLM has less stringent assumptions (homoscedasticity, compound symmetry, and sphericity), allows for missing data, tolerates differently spaced waves of data (e.g. due to Christmas breaks, Easter breaks), accounts for autocorrelation of residuals, and allows for nonlinear relations [31]. First, we started with a random intercept model (weeks are nested within students) as the baseline (not reported here). To address RQ2, we composed two models. The first model (M1) focused on comparing three groups of performance (baseline = passed students) overtime with the time spent on studying 'in advance' and 'catching up' as the outcomes.

$$\log(1 + y_{ti}) = \beta_{0i} + \beta_{1i}week_t + \beta_2 Excellent_i + \beta_3 Fail_i + e_{ti}$$
$$\beta_{0i} = \beta_0 + \mu_i$$
$$\beta_{1i} = \beta_1 + \mu_i$$

The second model (M2) took into account individual student characteristics (age, gender, education, occupation) and time variant characteristics (the designs of assimilative, productive, assessment activities). However, since demographics did not improve the overall fit of the model (based on the likelihood ratio test) [31], they were excluded in the end.

$$\log(1 + y_{ti}) = \beta_{0i} + \beta_{1i}week_t + \beta_2 Excellent_i + \beta_3 Fail_i + \beta_4 Assimilative_t + \beta_5 Productive_t + \beta_6 Assessment_t + e_{ti}$$
$$\beta_{0i} = \beta_0 + \mu_i$$
$$\beta_{1i} = \beta_1 + \mu_i$$

Where outcome y was in advance time or catchup time

Week t was nested within individual i

The analysis was done using the lme4 package [2] in R v.3.3.2 statistical package. Given our moderate sample size and balanced data, p-values were calculated using Type II Wald chi-square tests. A log transformation on the dependent variables (in advance time, and catchup time) was performed after examining the normality of the residuals. The assumptions of homoscedasticity, multicollinearity, residuals auto-correlation, and non-linearity were checked in all models which indicated there were no severe violations of these assumptions.

3 RESULTS

3.1 To what extent do students' timing of engagement align with instructor learning design?

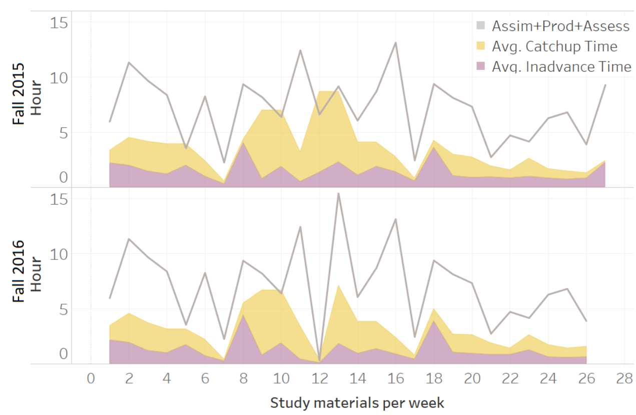
Fig. 1 illustrates the total time that students spent on study materials in the assigned week against the time recommended from the LD for the same materials. Compared to the LD (grey line), students in both semesters on average spent much less time studying in the VLE per week (M=3.59, SD=5.29 for 2015; M=3.17, SD=4.55 for 2016). In line with previous work [27, 29], the actual study patterns seemed to follow the same trends in the LD. Overall, students in both semesters spent on average more time studying the materials after the assigned week (catching up and revise) (M=2.14, SD=4.05 for 2015; M=1.91, SD=3.48 for 2016) than before the assigned week (in advance) (M=1.45, SD=3.09 for 2015; M=1.26, SD=2.82 for 2016), except for studying the materials in week 8, week 18, and week 27 (in Fall 2015), which was a TMA.

A closer look at the study patterns across the three different groups of performance (failed, passed, and excellent) was shown in Fig. 2a; Fig. 2b. Overall, given the same study materials, the passed and the excellent group of students spent more time on studying in advance and catch up than the failed students in both semesters (Fig. 2a; Fig. 2b). In Fall 2015, passed and excellent students spent on average each week 1.81 hours (SD=3.43), and 2.3 hours (SD=3.52) on studying in advance, compared to failed students with an average of 0.22 hours (SD=1.05). Similar trends in the time studying in advance across the three groups was also presented in Fall 2016. In Fall 2015, passed and excellent students followed a similar pattern studying in advance. However, in Fall 2016 passed and failed students portrayed a similar pattern for all study materials from week 1 to week 12. Since then, passed students spent more time studying in advance than failed students. A lot of time was spent on studying in advance in week 8, 18, and 27 (for Fall 2015) because of the respective assessments (TMAs) in these weeks (Fig. 2a).

Two study materials in weeks 9-10 (part 2.1) and weeks 12-13 (part 2.3) represented red-flags of overwhelming workloads, since they were associated with an increase in both studying in advance and catch up time (Fig. 2a; Fig. 2b). In Fall 2015, the passed and excellent students spent much more time to catch up on both of the materials, while the gap was smaller in 2016.

While excellent and passed students consistently spent more time studying both in advance and catch up than failed students, the relative frequencies revealed a different picture. In both semesters, all three groups of students spent a similar percentage of their time studying in advance in weeks which had a TMA (week 8, 18, 27) (Fig. 3a). However, in Fall 2015 failed students spent a higher proportion of their time on catching up activities (61% on average) than passed (56%) and excellent students (55%) in almost all weeks (Fig. 3b).

Figure 1: Time spent on study materials per week against the time recommended by instructor's learning design



In Fall 2016, the three groups shared a similar percentage of study time on catching up from week 1 to week 12. After week 12, failed students spent on average much higher proportion of their time on catching up activities compared to passed and excellent students (Fig. 3b). Towards the end of the course, the gap between failed and passed/excellent students increased considerably (Fig. 3b).

3.2 How do different levels of performance and learning design relate to different study patterns?

Compared to passed students, failed students spent significantly less time on studying in advance (B= -0.23, SE = 0.03, p<0.001) in 2015, while excellent students did not have any statistically significant difference (Table 2). A similar pattern was observed in 2016 for failed students (B= -0.14, SE = 0.03, p<0.001) while excellent students spent significantly more time on studying in advance (B = 0.12, SE = 0.03, p<0.001) (Table 2). Since we performed a log-transformation with the dependent variable, the coefficients should be exponentiated for meaningful interpretations. In other words, compared to passed students, the time spent on studying in advance will be 13.06% lower for failed students, and 12.75% higher for excellent students. After adding the LD (Model 2), the relations between different groups of performance and the time spent on studying in advance remained the same. In 2015, the higher the time designed for assimilative and assessment activities, the higher the time spent on studying in advance. A negative relation was found between productive

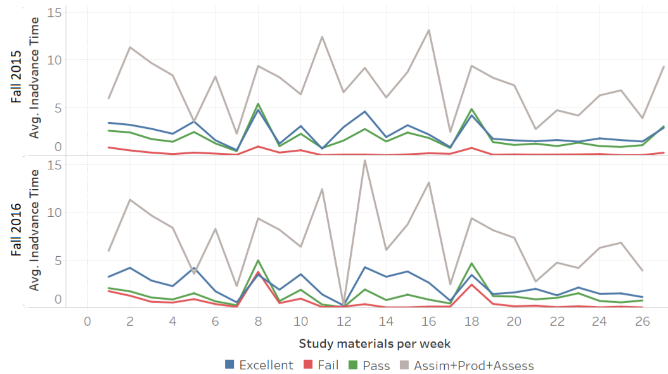


Figure 2a: Number of hours spent on studying in advance

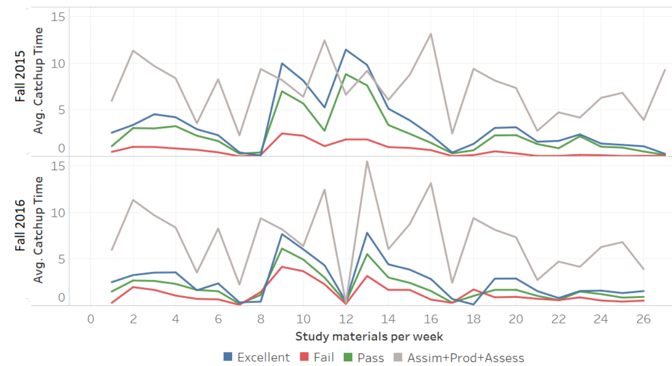


Figure 2b: Number of hours spent on studying catching up

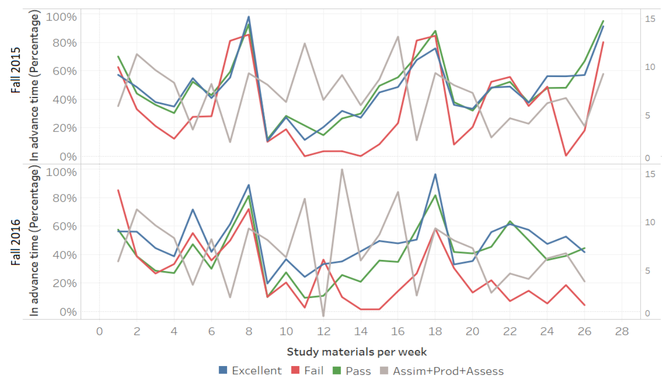


Figure 3a: Percentage of time spent on studying in advance

Figure 3b: Percentage of time spent on studying catching up

activities and the time spent on studying in advance. In 2016, the effects of assimilative and productive on the time spent on studying in advance were no longer significant. In other words, for one hour increase in assessment activities, we expect to see 3-4% increase in the time spent on studying in advance.

In line with our previous visualization (Fig. 2b), in 2015, compared to passed students, failed students spent significantly less time on studying catching up (B= -0.20, SE = 0.03, p<0.001), while excellent students spent significantly more time (B= 0.08, SE = 0.03, p<0.001) (Table 3). In other words, compared to the passed students, the time spent on catching up study was 22.14% lower for the failed students, and 8.33% higher for the excellent students. This catching-up could also be regarded as repeating particular learning activities, whereby a vast body of cognitive learning research has found that learning requires repetition. In a similar trend, in Fall 2016 compared to passed students, the time spent on catching up study was 12.75% lower for failed students, and 10.52% higher for excellent students. All the three types of learning activities had a significant relation with time spent on catching up. While the effect of assimilative and assessment activities was relatively small, one hour increase in productive activities was associated with 7.25% increase in the time spent on catching up.

4 DISCUSSION

4.1 How did students behave compared to the initial learning design?

In line with previous work [27, 29, 33], our findings indicated that the way instructors design for learning significantly influenced how student spent time on VLE. While in general the intended learning design and actual behaviours followed a similar trend over time, there remained substantial discrepancies between what instructors recommended or expected and the actual time spent on respective learning activities by students. In particular, in most weeks students spent less time (nearly a half) studying the assigned materials on the VLE compared to the number of hours recommended by instructors. One potential explanation could be that the time spent on VLE only partially represented the actual time spent overall, since students could study the same materials outside of the VLE (e.g., downloading PDF files, using other browsers). At the same time, in certain weeks the actual time spent on the assigned materials was equal or above the time recommended by instructors (i.e., week 9, 10, 12, 13). Given that the time spent on VLE only partially reflected the total time spent on the assigned materials, these discrepancies could signal a major

Table 2: Mixed effect model of time spent on studying in advance

	Fall 2015		Fall 2016	
	Model 1 B(SE)	Model 2 B(SE)	Model 1 B(SE)	Model 2 B(SE)
Fixed				
Intercept	.30(.02)	.30(.03)	.26(.02)	.20(.02)
Week	-.00(.00)**	-.00(.00)***	-.00(.00)***	-.00(.00)***
Fail	-.23(.03)***	-.23(.03)***	-.14(.03)***	-.14(.03)***
Excellent	.07(.04)	.07(.04)	.12(.03)***	.12(.03)***
Assimilative		.00(.00)*		.00(.00)
Productive		-.02(.00)***		.00(.00)
Assessment		.03(.00)***		.04(.00)***
Random				
Students	.06(.24)	.06(.24)	.05(.22)	.05(.23)
Week	.00(.01)	.00(.01)	.00(.01)	.00(.01)
LogLik	-470.8	-198.5	-550.2	-122.1
Obs	5103	5103	5148	5148
Students	189	189	198	198

*p<0.05; **p<0.01; ***p<0.001
Log-transformation on in advance time. Baseline = Passed students
Standard errors in parentheses for Fixed estimators
Standard deviation in parentheses for Random estimators

Table 3: Mixed effect model of time spent on studying catching up and revise

	Fall 2015		Fall 2016	
	Model 1 B(SE)	Model 2 B(SE)	Model 1 B(SE)	Model 2 B(SE)
Fixed				
Intercept	.46(.02)	.23(.03)	.40(.02)	.15(.02)
Week	-.01(.00)***	-.00(.00)***	-.01(.00)***	-.00(.00)***
Fail	-.20(.03)***	-.20(.03)***	-.12(.03)***	-.12(.03)***
Excellent	.08(.03)**	.08(.03)**	.10(.03)**	.10(.03)**
Assimilative		.01(.00)***		.01(.00)***
Productive		.07(.00)***		.09(.00)***
Assessment		-.00(.00)**		.01(.00)***
Random				
Students	.07(.26)	.07(.27)	.05(.22)	.05(.22)
Week	.00(.01)	.00(.01)	.00(.01)	.00(.01)
LogLik	-1222.8	-857.1	-1183.3	-711.5
Obs	5103	5103	5148	5148
Students	189	189	198	198

*p<0.05; **p<0.01; ***p<0.001
Log-transformation on catchup time. Baseline = Passed students
Standard errors in parentheses for Fixed estimators
Standard deviation in parentheses for Random estimators

underestimation of the actual workload of the assigned materials. This could potentially discourage and stress out students, given that the majority of the students in this course also had a part-time or full-time job, as well as potentially other responsibilities (i.e., family, caring responsibilities).

By comparing and contrasting the assumptions in LD made by instructors with actual student behaviour, LA could act as a reflective resource and provide actionable feedback. For example, instructors could adjust their expected workload of study materials in week 9, 10, 12, 13 and redistribute the workload more equally. At the same time, instructors could examine whether they overestimated the actual workload in week 16, as the LD allocated 13.13 hours while the actual time spent on the same materials on VLE was only 2.89 hours on average. However, adjusting the course schedule might not feasible in certain institutions, which require instructors to provide a detailed schedule in advance for quality-assurance purposes.

Secondly, our analyses have pointed out that the students' actual timing of study engagement could be substantially different from the assigned week. In particular, most students spent more time studying the materials after the week which they were assigned for. Therefore, given most students were also working in parallel to their study, LD should allow for more flexibility in the timing of the study. Moreover, instructors should take into account the whole learning process (planning, enacting, and revising) for each learning activity, rather than looking at a learning activity as a single entity occurred only in its assigned week.

One potential implication of our study could be that if students tend to spend more time on catching up a particular learning material, the instructors could check whether the material was clearly explained, and provide a quick recap or Q&A for the material in the subsequent weeks. For instance, students across all three groups of performance spent a lot of time catching up the study materials in week 13, which was a case study. Students continuously spent time catching up on this case study for five weeks after week 13. One explanation could be that many study activities after week 13 were based on this case study, therefore students tended to revisit this particular study material. Alternatively, they could revisit this case study as a part of the preparation for their TMA which was taken place in week 18. Finally, it could be due to the high workload or difficulty level in this case study which required several attempts to complete the task. In either way, the instructors could use this information to support their LD practice.

4.2 How do different levels of performance and learning design relate to different study patterns?

Not only did students exhibit different study patterns compared to the LD, these study patterns also varied significantly across our three groups of performance. Our analysis suggested that excellent students spent the highest amount of time studying on VLE, followed by passed students and failed students. One obvious interpretation could be that the more effort ones put in, the higher the respective learning results will be. However, since the time spent on VLE only partially captured the total effort, another explanation could be that students who studied on VLE had better results than the students who studied on other platforms (e.g., engagement in Facebook on informal learning communities is not tracked by the OU).

Even though this order of engagement intensity across the three groups remained the same in both in advance and catching up study patterns, their relative frequency revealed a different story. Given the same study materials, excellent students spent a large share amount of time studying in advance, while failed students spent a large proportion of their study time on catching up. These differences became even more prominent towards the end of the course, in which 80-100% of the time spent on the material by failed students was catching up activities, compared to 40-60% for passed and excellent students (Fig. 2b). Interestingly, for the first 10 weeks failed, passed, and excellent students spent roughly the same percentage of study time on catching up. An important implication of this could be that instructors should pay careful attention to students with a high percentage of catching up behaviour from week 10 onwards, as that could be a signal of the students falling behind with their study. Alternatively, providing different pacing or study breaks for students might allow "failing" students to catch a breath, and continue successfully afterwards.

Furthermore, each type of learning activities could significantly influence how much time students study in advance or catching up. For instance, for assessment activities (such as TMAs), all the three groups of students spent 80-100% of their time studying in advance, with the exception in week 18 in 2016 (Fig. 3b) when failed students spent on average only 60% of the time studying in advance for assessments. However, for productive activities, students were more likely to delay their action (one hour increase in productive activities was associated with 7.25% increase in the catching up time). Therefore, instructors in this course could re-examine the design of the productive activities.

Last but not least, while the analysis has shown significant relations between different types of learning activities, different study patterns, and different groups of performance, we also need to keep in mind that learners are agents. Given the same demographics (age, sex, gender, occupation, education) and the same study pattern, different students might still end up with different results. For example, there was 5-6% random variance across individuals with a standard deviation ranging from 24-30% (Table 3). In other words, if student A who spent 30% more or less on studying in advance or catching up than student B, both could still achieve the same outcome (pass the course) in the end.

5 CONCLUSIONS & IMPLICATIONS

In conclusion, this study investigated how students actually study compared to the initial learning design, and how different groups of performance and LD were related to these study patterns. Our analyses were conducted using trace data from the VLE longitudinally over 28 weeks, on 387 students, and replicated over two semesters in 2015 and 2016. Our findings indicated that there were discrepancies between how instructors designed for learning and how students studied in reality. In particular, given the same materials, the time spent on VLE was on average less than the number of hours recommended by instructors in most weeks. The analysis also pointed out that the timing of study could take place before, during, or after the assigned week. The actual study patterns also varied across different groups of performance. Excellent students on average spent more time studying both in advance and catching up than passed and failed students. At the same time, the percentage of time spent on catching up activities was higher for failed students compared to passed and excellent students. Finally, different types of learning activities could influence how study studied in advance or catching up.

From a research perspective, this study contributes to the literature by providing empirical evidence of how and when students study compared to the recommended path designed by instructors. Our findings reinforced the vital position of LD in the context of LA. Firstly, it is important to incorporate the LD for methodological purpose as it could support LA researchers to refine their measurements (i.e. time-on-task estimation). Although this study only partially addressed this issue of measurement, we encourage future scholars to tailor their duration limit of time-on-task to the content and design of individual activity. Secondly, the inclusion of LD in the analysis could help both researchers and practitioners to better interpret the results. Thirdly, our study showed the importance of temporal characteristics of engagement in LA research, as this could provide a deeper understanding of the learning processes compared to studies with aggregated engagement metrics.

From an instructor perspective, this study makes a step forward to translate LA findings into actionable feedback [36]. By having a better understanding of how, when students study on which materials, and how these behavioural patterns connected to LD, instructors may be in a much better position to reflect and adjust their teaching practices. By explicitly pointing out which study materials were under or over-used, instructors can take action on these materials. Our findings also emphasize the need to keep in mind the whole learning process for each learning activity when designing their course, rather than seeing each activity as a single occasion in its assigned week.

From a learner perspective, visualizations of the timing of engagements of peers could act as practical guidelines for students with different learning preferences, and support them to self-regulate their learning (e.g., plan their study time) more efficiently. For example, if the previous cohort spent a lot of time catching up on a particular week or study material, then a new cohort of students can either start studying the materials earlier, or reserve more time for catching up in the following weeks. Moreover, students can make use of their own LA visualizations to keep track of their study plan. For instance, students could set up their own study plans (how much time do I spend on this material, what is my deadline, etc.) and use LA visualizations of their actual study behaviour to continuously reflect on their study plans (do I overestimate or underestimate the actual workload, am I following or falling behind with the course schedule, etc.).

Last but not least, there are some limitations of the current study that readers keep in mind for future research. Firstly, our study was conducted within the context of one online module, which could restrict the generalizability of the study to another context. Our study only took into account students who completed the course for comparison purposes, while students who withdrew might offer additional insights into the findings. Secondly, while the LD taxonomy has been developed and implemented at the OU for a long period, it could over-simplify the actual LD (i.e. multiple types of assessment such as formative, summative, self-assessment were collapsed into one category). At the same time, keeping a taxonomy concise to be able to generalise to other contexts, yet, detailed to separate different types of learning activities remains a challenging task. Finally, it is important to acknowledge the caveats of using trace data on VLE. While the student behaviour on VLE has contributed to the increasing accuracy of the predictive algorithm of student performance, of course, it does not capture student behaviour outside of VLE or offline.

Our study has pointed out some potential issues that instructors could pay attention to. However, further qualitative research is needed (interview with instructors and students), in order to identify the underlying reasons behind these inconsistencies between LD and actual behaviours. Nonetheless, our research clearly points towards the need for LA researchers to take time into consideration when modelling LA and LD in particular.

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