Unravelling the dynamics of instructional practice: A longitudinal study on learning design and VLE activities

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ABSTRACT
Substantial progress has been made in understanding how teachers design for learning. However, there remains a paucity of evidence of the actual students' response towards leaning designs. Learning analytics has the power to provide just-in-time support, especially when predictive analytics is married with the way teachers have designed their course, or so-called a learning design. This study investigates how learning designs are configured over time and their impact on student activities by analyzing longitudinal data of 38 modules with a total of 43,099 registered students over 30 weeks at the Open University UK, using social network analysis and panel data analysis. Our analysis unpacked dynamic configurations of learning designs between modules over time, which allows teachers to reflect on their practice in order to anticipate problems and make informed interventions. Furthermore, by controlling for the heterogeneity between modules, our results indicated that learning designs were able to explain up to 60% of the variability in student online activities, which reinforced the importance of pedagogical context in learning analytics.

CSS Concepts
•Applied computing → E-learning; Distance learning

Keywords
Learning analytics, learning design, social network analysis, longitudinal, panel data analysis

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1. INTRODUCTION
In the last decade, there is a growing body of literature [11, 15, 32] that seeks to develop a descriptive framework to capture teaching, and learning activities so that teaching ideas can be shared and reused from one educator to another, so called Learning Design (LD) [16]. A common metaphor of a learning design was a music notation which contains enough information to convey musical ideas from one to another over time and space [16]. Extensive research has been conducted focusing on technological implementations of LD such as the Educational Modelling Language (EML) [29], the SoURCE project [31], the Australian Universities Teaching Council (AUTC) LD project [1], and the Learning Activity Management System (LAMS) [14]. While the early work in LD have focused on transferring the design for learning from implicit to explicit, the relationship between LD and the actual learners' response has been not fully understood. As the majority of feedback takes forms of assessments, and course's evaluations, which typically takes place after the learning process has finished, it prevents teachers from making in-time interventions. Recently, the advancement in technology has allowed us to capture the digital footprints of learning activities from Virtual Learning Environment (VLE). This rich and fine-grained data about the actual learners' behaviors offer educators potentially valuable insights on how students react to different LDs.

Learning analytics (LA) has the potential to empower teachers and students by identifying patterns and trends from a wide variety of learners' data. Within the LAK community, substantial progress has been made both in conceptual development [10, 17] as well as how to design appropriate predictive learning analytics to support students [19, 26]. Nonetheless, in line with [26, 44] findings from LA research in the past have been rather limited to delivering actionable feedback, while ignoring the context of which the learning data is situated. Thus, within the LAK community there is an increasing interest to align LA with LD, as the former facilitates the transfer of tacit educational practice to an explicit rendition, while the latter provides educators with pedagogical context for interpreting and translating LA findings to direct interventions [3, 33, 34, 37, 40]. While there are abundant discussions on the value and impact of integrating LD into LA to improve teacher inquiry [3, 37], only a few studies have empirically examined how teachers actually design their courses [4, 20] and whether LD influences satisfaction, VLE behavior, and retention [42, 44, 45, 48]. However, most previous studies are limited to interviews and experimental settings, while others have only explored LD from a static perspective, without accounting for the differences within and between modules and the possible interaction between different types of learning activities over time.

This study builds on previous work by Rienties and Toetenel [45], [48] by dynamically investigating the use of learning design in 38 modules over 30 weeks at one of the largest distance higher education institutions in Europe using social network analysis and panel data analysis. Our work contributes to the existing LA literature by capturing: (1) how teachers configure their course over time, (2) how learning activities interact with each other across modules, and (3) how learning designs help to explain VLE behavior over time.

2. ALIGNING LA WITH LD

In the last five years, LA has attracted a lot of attention from practitioners, management, and researchers in education by shedding light on a massive amount of (potentially) valuable data in education, as well as providing means to explicitly test existing pedagogical theories. Scholars in the field of LA have exploited various sources of data, such as activity logs of students [35], learning dispositions [7, 39], or discussion forum [2, 51]. By taking advantage of advanced analytical techniques such as predictive modeling [46], discourse analytics [49], machine learning [30], and so on, LA has succeeded in uncovering meaningful patterns and trends occurred during the learning process. While these studies provide important markers on the potential of LA in education, critics have indicated a gap between pedagogy and LA [18, 28, 50]. Interesting patterns can be identified from student activities, such as number of clicks, discussion posts, or essays. However, these patterns alone are not sufficient to offer feedback that teachers can put into actions [19, 43]. Without a pedagogically sound approach to data, LA researchers may struggle with deciding which variables to attend to, how to generalize the results to other contexts, and how to translate their findings to actions [28]. Hence, LD can equip researchers with a narrative behind their numbers, and convert trends of data into meaningful understandings and opportunities to make sensible interventions.

The core concepts of LD are best summarized in the Learning Design Conceptual Map (LD-CM) (Figure 1). It starts with the main objective of "creating learning experiences aligned to particular pedagogical approaches and learning objectives". How educators make decision about designing for learning is determined by Characteristics & Values of the learning environment, the educational philosophy, and theories and methodologies. In a interview based study of 30 participants, Bennett, Agostinho and Lockyer [4] identified three main factors that influenced how teachers engage in the designing process: student-related factors (cohort profile, learning objectives, feedback from past sessions), teachers-related factors (beliefs about teaching, prior experiences), and context-related factors (colleagues, institutional policies and culture, resources such as workload, time, and infrastructure).

In the teaching cycle, the reflection phase is limited to insights generated from assessments, course evaluations, and self-reports. These channels may suffer from selection bias, response bias, and hinder educators to make in-time interventions. A potential contribution of LA in LD is to include real-time learner response to a LD, such as how much time was spent on a particular activity, or how often a student visits a concept/topic. These behavioral traces allow educators to both make personalized interventions to each student as well as adjust the course according to the overall trends of a group of students. As illustrated below, LA allows educators to reflect and compare their practice in a wide range of granularity: from learning activities to modules, and disciplines. Overall, using LA in combination with other feedback channels, such as assessment and evaluation, could empower and speed up the teaching cycle by generating more feedback, allow educators to make in-time interventions, to reflect, and to compare their practice on multiple levels of granularity.

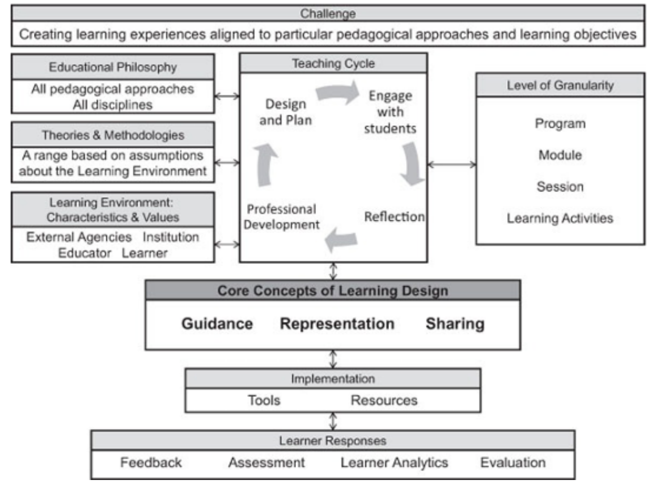


Figure 1: A Learning Design Conceptual Map. Retrieved from Dalziel, Conole, Wills, Walker, Bennett, Dobozy, Cameron, Badilescu-Buga and Bower [16].

2.1 Connecting LD and LA

Since the beginning of the 21st century, the term learning design has emerged as a "methodology for enabling teachers/designers to make more informed decisions in how they go about designing learning activities and interventions, which is pedagogically informed and makes effective use of appropriate resources and technologies" [11]. For more discussion on the origins of 'learning design' and 'instructional design', we refer readers to Persico and Pozzi [40]. Several approaches for designing learning have been proposed, yet, one common stage in almost every approach was the evaluation of the LD [36, 40]. Persico and Pozzi [40] argued that the learning process should not only depend on experience, or best practice of colleagues but also pre-existing aggregated data on students' engagement, progression, and achievement. In a similar manner, Mor, Ferguson and Wasson [37] suggested that LA could facilitate teacher inquiry by transforming knowledge from tacit to explicit, and perceive students and teachers as participants of a reflective practice. For instance, in a study of 148 learning designs by Toetenel and Rienties [47], the introduction of a systematic LD initiative consisting of visualization of initial LDs and workshops helped educators to focus on the development of a range of skills and more balanced LDs. Feeding information on how students are engaged in a certain LD during or post-implementation can provide a more holistic perspective of the impact of learning activities [34].

Several conceptual frameworks aiming at connecting LA with LD have been proposed. For example, Persico and Pozzi [40] discussed three dimensions of LD that can be informed by LA: representations, tools, and approaches. Lockyer, Heathcote and Dawson [34] introduced two categories of analytics applications: checkpoint analytics to determine whether students have met the prerequisites for learning by assessing relevant learning resources, and process analytics to capture how learners are carrying out their tasks. In the recent LAK conference 2016, Bakharia, Corrin, de Barba, Kennedy, Gašević, Mulder, Williams, Dawson and Lockyer [3] proposed four types of analytics (temporal, tool specific, cohort, and comparative), and contingency and intervention support tools with the teacher playing a central role.

In this paper, we will use the conceptual framework developed by Conole [11] and further developed by Rienties & Toetenel (REF). Both conceptual and empirical research has found that the Open University Learning Design Initiative (OULDI) can accurately and reliably determine how teachers design courses, and how students are subsequently using these LDs [45, 48]. Seven types of learning activities can be found in Table 1. *Assimilative* activities refer to tasks which require learner's attention to information. These include watching lecture video, reading the text, listening to an audio file, etc. *Finding and handling information* activities implies, for example, searching and filtering for relevant literature in a particular topic on the internet. *Communication* activities refer to a range of practices to communicate such as posting in a discussion forum and replying to peer comments. *Productive* activities represent the construction of an artifact, such as writing a summary or resolving a problem. *Experiential* activities provide learners with opportunities to apply theories in a real-world setting such as case study, or field trip. *Interactive/adaptive* activities encourage learners to apply what they learned in an experietial environment, or interactng with a simulation. Finally, *assessment* activities evaluate the learner's understanding such as writing through the construction of an essay, exam or making a presentation.

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 (summarive, formative and self assessment)	Write, Present, Report, Demonstrate, Critique.

Source: Retrieved from Rienties and Toetenel [45]

While there were numerous discussions in aligning LA with LD, the amount of empirical studies on the subject has been rather limited. For example, Gašević, Dawson, Rogers and Gasevic [19] examined the extent to which instructional conditions influence the prediction of academic success in nine undergraduate courses offered in a blended learning model. The results suggested that it is imperative for LA to taking into account instructional conditions across disciplines and course to avoid over-estimation or underestimation of the effect of LMS behavior on academic success. From our observation, most of the empirical studies attempting to connect LA and LD are derived from students activities [34], or differences in discipline [19], rather than how teachers actually design their course [24].

In our previous work, we have highlighted explicitly the role of LD in explaining LMS behavior, student satisfaction, retention, and differences in prediction of academic success [19, 42, 44, 45, 48]. For example, in our first study linking 40 LDs with VLE behavior and retention, we found that strongly assimilative designs (i.e., lots of passive reading and watching of materials) were negatively correlated with retention [42]. In a large-scale follow-up study using a larger sample of 151 modules and multiple regression analyses of 111,256 students at the Open University, UK, Rienties and Toetenel [45] revealed relations between LD activities and VLE behavior, student satisfaction, and retention. The findings showed that taking the context of LD into account could increase the predictive power by 10-20%. Furthermore, from a practitioner's perspective, the combination of a collaborative, networked approach at the initial design stage, augmented with visualizations, changed the way educators design their courses [47]. While these three studies at the Open University UK (OU) highlighted the potential affordances of marrying LD with LA on a large scale, two obvious limitations of these studies were the aggregation of learning activities in predicting behavior and performance (i.e., rather than their interaction), as well as the static rather than longitudinal perspective of LD. In these studies [42, 44], aggregate learning design data across the 40 weeks of each module were used, while in many instances teachers use different combinations of learning activities throughout the module [24]. While fine-grained longitudinal data of LD per week were not available during the initial implementation phase of LD at the OU, in the last year fine-grained weekly LD data has been added, which would allow us to potentially identify the optimum mix of LD activities per discipline, level, and type of students per week and over time.

2.2 Research Questions

Building on previous conceptual and empirical research, we are particularly interested in how teachers design their learning activities over time since learning is a dynamic and time-variant process. Hence, our first research question is:

1) How are learning designs configured across modules over time?

Prior studies of Social Network Analysis (SNA) in e-learning, particularly in the improvement of LD have concentrated on examining patterns of learner communication and collaboration in various situations, such as when discussing, blogging and e-mailing [8]. Within the last three years in LA, SNA has been shown to be an effective tool to explore the relationships of learners in online discussion forum [9, 23, 25, 27, 41], or in eye tracking movements [52]. However, none has looked at the LD from a social network perspective on a large scale study. Hora and Ferrare [24] suggested that teaching practice should be best viewed as situated in and distributed among features of particular settings. According to the systems-of-practice theory by Halverson [21], local practices are informed, constrained, and constituted by the dynamic interplay of artifact and tasks. Thus, in order to understand how teachers design their course, it is necessary to consider the inter-relationships among different learning activities. Thus, our next research question aims at examining:

2) How do different learning activities interact with each other across modules?

Finally, our previous work has indicated that learning designs are strong predictors of VLE behaviors [45, 48]. However, we did not take into account the differences between modules which might affect the robustness of the analysis [19]. Hence using panel data analysis, we investigate:

3) How do learning designs affect VLE behavior over time?

3. METHOD

3.1 Setting

This study took place at the OU, which is the largest distance education provider in Europe. Data in this study was generated from OULDI, 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 [13]. When using data to compare module design across disciplines and modules, according to our previous work [45, 48] it is important to classify learning activities in an objective and consistent manner. 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. 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. 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 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. To sum up, the mapping process is reviewed by at least three people to ensure the reliability and robustness of the data relating to a learning design.

In this study, of 56 modules were selected with all contained LD data that have been documented on a weekly basis for the academic years 2014 and 2015, we ended up with 42 modules after excluding 14 modules that were short, intensive training modules. The final selection of modules were equally distributed across a range of disciplines with 21% in Art & Social Sciences, 21% in Business & Law, 12% in Education, Languages, and Health studies, 22% in Science and Technology, and 24% in other disciplines. Over 90% of the modules were undergraduate courses. There were 20 modules with 60 credits, 19 modules with 30 credits and 3 modules with missing information.

In preparation for the panel data analysis, we linked 42 modules with weekly LD data in 2014 and 2015 with weekly VLE data, whereby 38 modules were successfully merged. The average number of students registered in each module was 1134 with the minimum of 75 and the maximum of 3707. On average, 91% of the students who followed the course until the end passed (SD = 0.058) while 63.4% of all the registered students passed the course (SD=0.086). The retention rate of all the modules was 69% on average, with a range from 56% to 85%.

3.2 Instruments

3.2.1 Measurement of learning designs

Seven LD variables were measured in terms of workload, which is the number of hours that students are expected to study. Time spent on learning activities was restricted based on the size of the module, such as 30 credits equated to 300 hours of learning, and 60 credits equated to 600 hours of learning. Of the 38 modules, students were expected to study on average 8.10 hours per week, of which 3.92 hours were spent on assimilative activities, 0.26 hours on finding information, 0.29 hours on communication, 1.32 hours on productive activities, 0.14 hours on experiential activities, 0.17 hours on interactive activities, and 1.99 hours on assessment.

3.2.2 Measurement of VLE

In line with Tempelaar, Rienties and Giesbers [46] and our previous works [45], two different types of VLE data were gathered per module in a static and dynamic manner: average time spent (in minutes) on VLE per week (M=115.4, SD=88.4), and average time spent per visit (in minutes) on VLE (M=22.5, SD=8.7). Even though learner activities on VLE were recorded in 40 weeks, we only used the first 30 weeks data in parallel with 30 weeks data of learning designs. It should be noted that these crude measurements of VLE only represented the average time a student spent on VLE platform, not the actual studying time, as this can be affected by unobservable factors, such as when students study offline, or using non-OU systems such as Facebook (which the OU does not monitor).

3.3 Data analysis

3.3.1 Visualization of learning designs over time

We used Tableau to visualize the LD of 42 modules over 30 weeks of study time. We displayed both static and dynamic representations of LD of which the former aggregated all modules, while the latter was per module basis.

3.3.2 Social network analysis

In line with [24], we used SNA to study the relationships among learning activities as this technique enables us to quantify and visualize the interactions and connections between the seven learning activities. The LD dataset was a weighted two-mode network as it consisted of different learning activities across several weeks as illustrated in Figure 2 below. Since we are primarily interested in the relationships among learning activities, the dataset was transformed to a one-mode network in line with Hora and Ferrare [24].

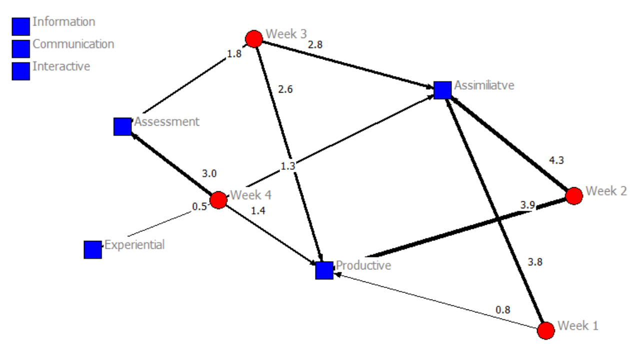


Figure 2: Weighted two-mode network of module X across the first five weeks

Firstly, two learning activities (blue nodes) become connected if they were present in the same week (red nodes). Since we captured how much time students were expected to spent on each LD each week, the weights of the two learning activities had directed towards identical weeks could also be measured. In this type of projected network, the weight of a tie from one LD to another was not necessarily equal to the weight of the reverse. For example, in Figure 2, if 2.8 hours were spent on assimilative activities and 1.8 were spent on assessment activities in the same week, then the weight from assimilative to assessment is recorded as 2.8 and the weight of the reverse is recorded as 1.8.

Second, the weight of each tie was discounted for the number of learning activities in the same week [38]. It can be argued that the tie between two learning activities is weaker when there are more learning activities that are present in the same week. This can be generalized as follows:

$$w_{ij} = \sum_{p} \frac{w_i p}{N_p - 1}$$

where w_{ij} is the weight between LD i and LD j, and N_p is the number of learning activities in week p.

After transforming the dataset, we used the Netdraw function of UCINET [5] to visualize the co-occurrences between each pair of learning activities across all weeks. The nodes represent the different learning activities. The tie represents the co-occurrence of two learning activities in the same week. The thickness of the line reflects the strength of the ties. Thus, the thicker the line, the higher the weights of the tie between two learning activities, which was also represented by the numbers attached along the line.

Finally, in line with Hora and Ferrare [24] configurations of co-occurring learning activities within each module were used to determine the repertoires of practice. These were computed as the combinations of learning activities that occurred most frequently.

3.3.3 Panel data analysis

In preparation for the analysis, the two datasets on LD and VLE were transformed from wide to long format. Additional identifiers were generated as the combination of course code, presentation, and week. The next step was to merge this dataset according to these new identifiers. Next, a Hausman test was used to differentiate between fixed effects and random effects model. It tests whether the coefficients estimated by the efficient random effects estimator are the same as the ones estimated by the consistent fixed effects estimator [22]. Our result supported the assumption of correlation between observation's errors and predictors, hence, fixed effects model was used as it removes the effect of time-invariant characteristics to assess the net effect of the predictors on the outcome. Our analysis was done in Stata.

4. RESULTS

4.1 How are learning designs configured across modules over time?

Figure 3 illustrates the average time students were expected to spend per module (in hours) on different learning activities over 30 weeks.

At a glance, we can see that there were a lot of fluctuations in learning activities over time, which indicated a dynamic usage of LD from teachers (Figure 3). Aligned with previous findings [42, 44, 45, 47, 48], assimilative activities accounted for the majority of learning time (M=3.9, SD=3.4), which were followed by assessment activities (M=2.0, SD=3.5). In other words, students were expected to spend around 6 hours per week on "traditional" learning activities of reading and watching materials, and completing formative and summative assessments. Productive activities were also adopted constantly over time (M=1.3, SD=1.7). Communication, experiential, interactive, and finding information activities were underused most of the time. Interestingly, assessment and assimilative activities followed opposite paths in which more assimilative activities were used at the beginning of a module whereas more assessments were used toward the end. There seems to be no correlation of any LD with the total time spent indicating that there is no systematic bias in favoring a particular learning design.

After capturing the dynamic picture of LD over time, we took a further step to examine how different learning activities are configured across different modules. Due to the limited space, we only reported three exemplar modules across three disciplines with a variety of configurations and patterns of learning activities (Figure 4).

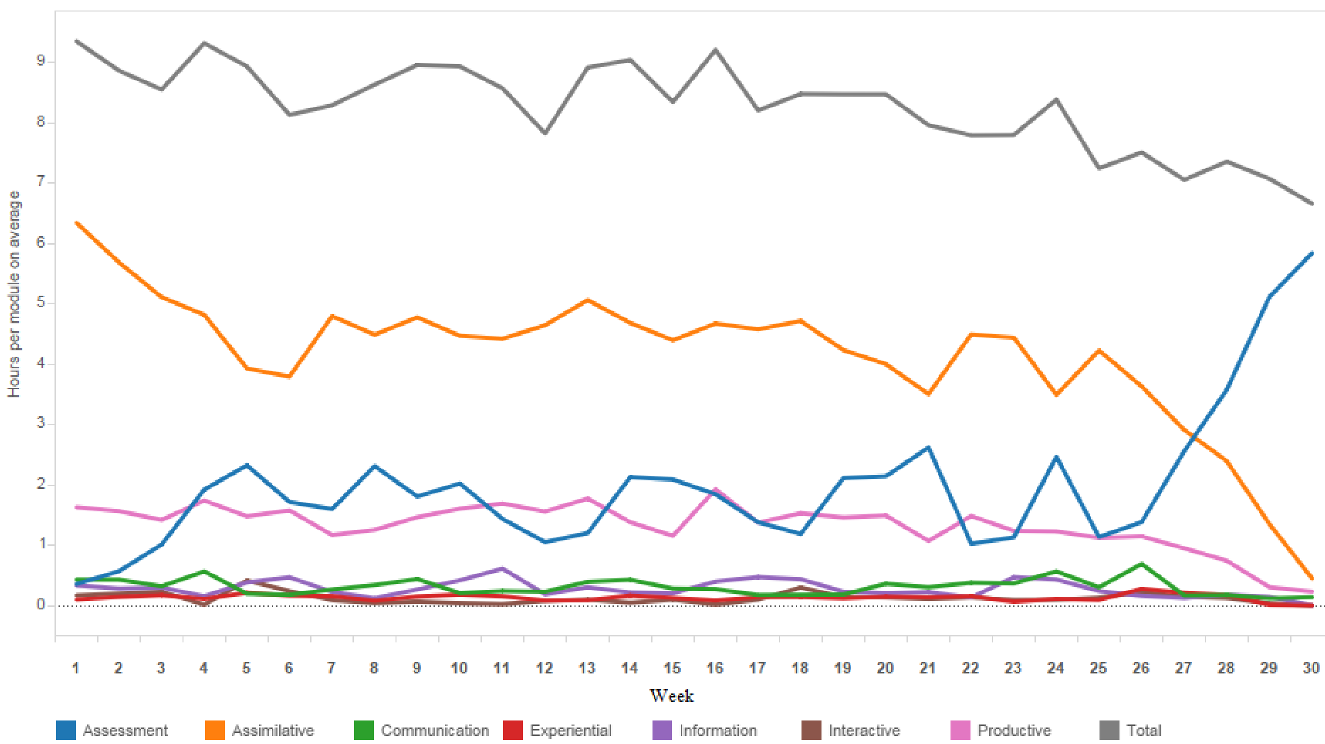


Figure 3: Learning designs of 42 modules over 30 weeks in 2014 & 2015

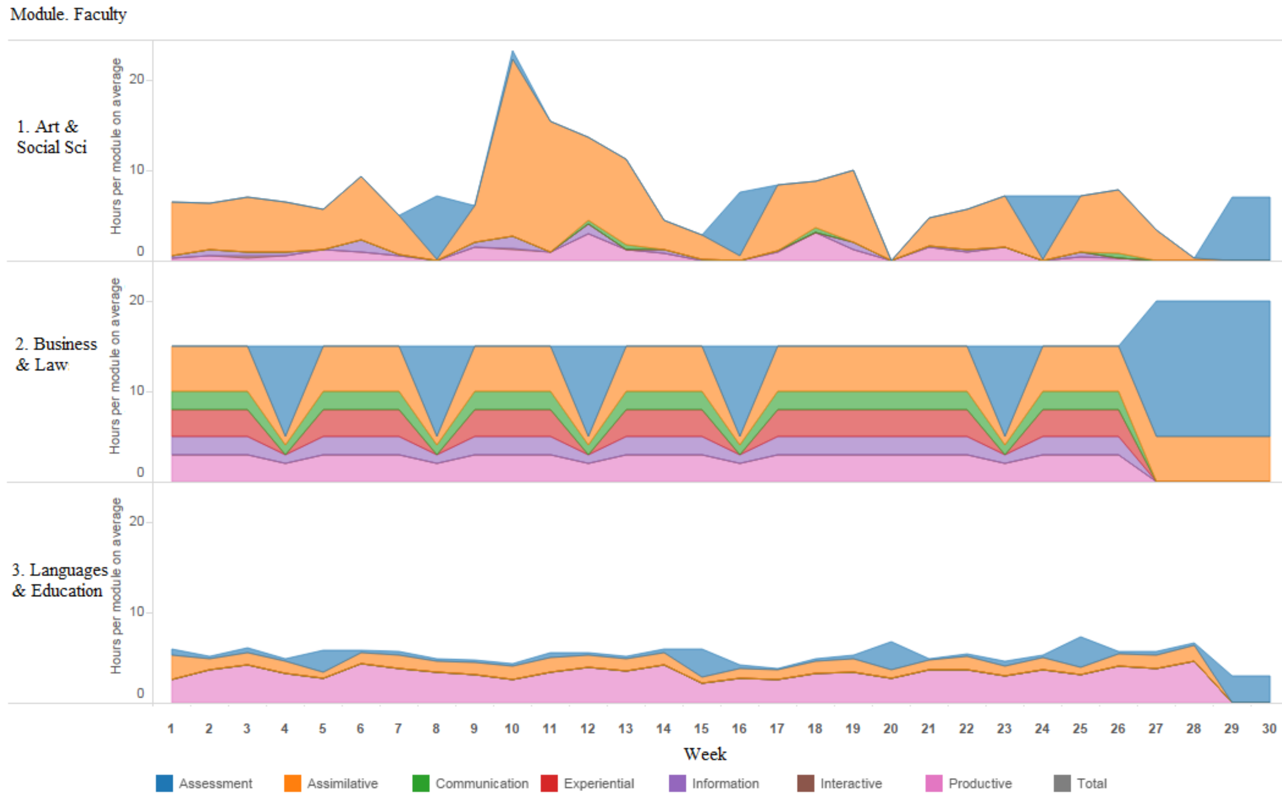
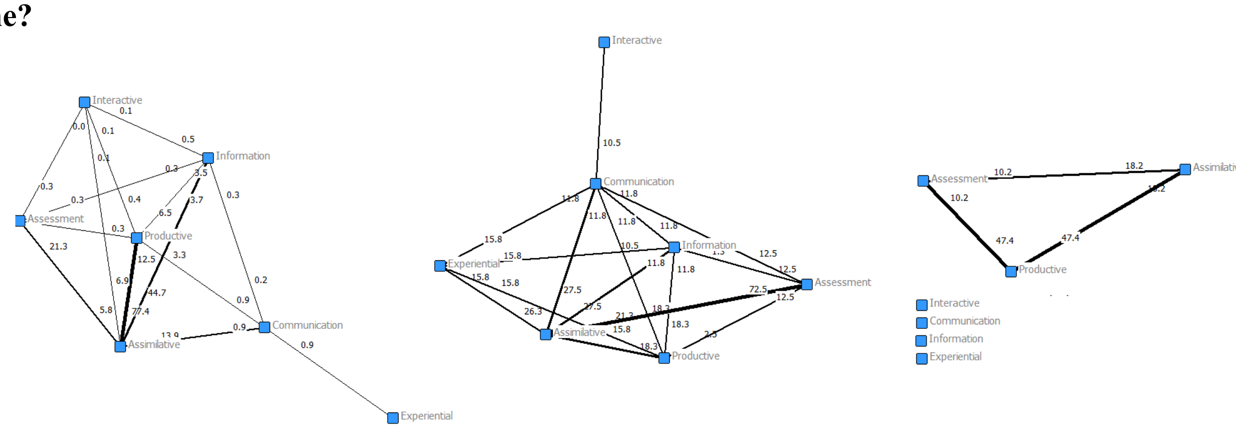


Figure 4: Feature modules

A closer look at each module revealed a diversity of combinations of LD over time. Module 1 in Arts & Social Science confirmed the dominance of assimilative (M=4.9, SD= 4.3) and assessment activities (M=1.4, SD=2.8). Remarkably, there was a surge in the assimilative activities up to 19.6 hours in week 10 and 14.4 hours in week 11. On the other hand, module 2 in Business and Law represented a more balanced learning design. The total workload of 15 hours each week remained constant throughout 30 weeks with the exception of week 30 where students were expected to spend more time on assessment activities. There was an assessment almost every 3 weeks of study. Students in this module engaged in multiple learning activities: assimilative (M=4.3, SD=1.5), communication (M=1.6, SD=0.7), finding information (M=1.6, SD=0.7), productive (M=2.4, SD=1.04), experiential (M=2.1, SD=1.4), and assessment (M=3.7, SD=5.9). Finally, module 3 used only three types of LD over time: assimilative, assessment, and productive. The workload of module 3 in Languages and Education stayed relatively constant over time, with the majority of studying time are dedicated to productive activities.

4.2 How do different learning activities interact with each other across modules over time?



1. Art & Social Science	2. Business & Law	3. Languages and Education

Figure 5: Social network analysis of learning designs

Our social network analysis reveals a variety of combinations of LD across modules. Again, due to the limited space, we only reported the three aforementioned exemplar modules (Figure 5).

In Module 1 in Art & Social Sciences, assimilative activities displayed strong connections with productive and finding information while there were weak links among other learning activities. Furthermore, communication acted as a gatekeeper between experiential and other learning activities which implied communication was the necessary condition for the existence of experiential activities. This module confirmed the dominance of assimilative design as previously illustrated in Figure 3. The density of the network was 64% with 13 ties in total. The average distance among reachable pairs was 1.306. The most frequently used repertoire of practice was assimilative, information, and productive (38.7% of the time). The relationships among learning activities in module 2 were more equally distributed in the network, with the exception of interactive.

Module 2 in Business and Law demonstrated a repertoire of practice that frequently used assimilative, information, communication, The network density of this module was 67% with 14 ties in total. The average distance among pairs was 1.2. Assimilative and assessment shared the strongest connection. Again, communication played a gatekeeping role in this module in which it facilitated the use of interactive activities, experiential, and productive activities (70% of the time).

Module 3 in Languages and Education exhibited a unique setting which consisted of only three learning activities: assimilative, assessment, and productive. The network density was 14.3% with 3 ties, and the average distance was 1. Evidently, the most frequently used repertoire of practice in this module was assimilative, assessment, and productive (90% of the time).

4.3 How do learning designs affect VLE behavior over time?

In this section, we examined how different learning activities influence average time spent on VLE per visit (Table 2), and on VLE per week (Table 3).

For each predictors, four models were applied. First, we ran normal OLS regression model. Second, we used fixed effect model to the control of the unobserved heterogeneity of time. Third, we controlled for the fixed effect across modules. Finally, we controlled for the fixed effects of both time and modules. The baseline for LD is the assimilative type. Thus, all the following results should be interpreted relatively to the module with the assimilative design. Variance inflation factor (VIF) was computed after each model to check for multicollinearity. The result indicated there were no significant correlations among the independent variables, in other words, there was no overlap of measurements among seven learning activities. Unstandardized coefficients were reported because all the explanatory variables were measured in the same unit (hours). Thus, it is more informative to report the original metrics. In the first and second model (Table 2), the effects of each independent variable remained relatively the same . It implied that there were no heterogeneity overtime. Assessment, communication, and productive were positive and significantly associated with VLE per visit. However, the predictive power of these models was relatively weak, which only explained 7%-8% of the variability. In contrast, the predictive power of LD on VLE increased noticeably when taking into account the differences across module (model 3 & 4). The effect of assessment became smaller and insignificant.

Table 2: Panel data analysis of the effect of learning design on the average time spent on VLE per visit

	(1)	(2)	(3)	(4)
VLE_per_visit	OLS	FE_ week	FE_ module	FE_module _week
Assessment	.51***	.51***	.03	.04
	(.08)	(.08)	(.06)	(.06)
Information	.25	.32	-.05	.007
	(.35)	(.35)	(.24)	(.24)
Communication	2.16***	2.16***	.69***	.68***
	(.35)	(.35)	(.26)	(.26)
Productive	.49***	.52***	-.34***	-.32**
	(.16)	(.16)	(.13)	(.13)
Experiential	-.13	-.13	-.55	-.53
	(.53)	(.53)	(.37)	(.36)
Interactive	.50	.48	.17	.14
	(.34)	(.34)	(.24)	(.24)
Constant	20.19***	20.11***	22.74***	19.29***
	(.40)	(0.40)	(0.31)	(1.28)
Observations	1,114	1,114	1,114	1,114
Adjusted R-squared	0.07	0.08	0.60	0.63

Unstandardized betas, Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The effect of communication also decreased to 0.69, which implied that on average an extra hour spent on communication activities is associated with 0.69 minutes increase in the time spent per visit on VLE. In contrast to model 1 & 2, productive activities negatively impacted VLE per visit. On average, an additional hour spent on productive activities was associated with 0.34 minutes less in time spent on VLE per visit. By controlling of the unobservable heterogeneity across modules, LD can explain up to 60% of the variability in time spent on VLE per visit. Our results validated the importance of taking into account the learning context of each module.

A similar trend was observed in predicting the average time spent on VLE per week in Table 3. In model 1 & 2, assessment, communication, and interactive were positive and significantly related with VLE per week. In model 3 & 4, the effect of assessment and communication became smaller and insignificant. Productive activities were negatively associated with VLE per week. Students who spent one extra hour spent on productive activities on average spent 4.42 minutes less in VLE. The positive effect of interactive activities weakened. An additional hour spent in interactive activities was associated with 6.17 minutes increase in VLE. Moreover, more time spent on experiential was associated with less time on VLE per week. An extra hour spent on experiential activities was associated with 8.43 minutes decrease in VLE. The predictive power of LD on VLE per week increased largely when taking into account the differences between modules (Adj-R2 = 40%). Similar models were run again with assessment as the reference level, however, there was no significant effect of assimilative activities on both VLE per week and VLE per visit.

Table 3: Panel data analysis of the effect of learning design on the average time spent on VLE per week

VLE_per_week	(1) OLS	(2) FE_ week	(3) FE_ module	(4) FE_module _week
Assessment	2.96***	2.35***	-.49	-.98
	(.79)	(.83)	(.74)	(.75)
Information	4.442	5.192	.30	.72
	(3.60)	(3.60)	(3.10)	(3.04)
Communication	16.53***	16.40***	4.32	3.79
	(3.60)	(3.57)	(3.39)	(3.31)
Productive	.74	1.73	-5.63***	-4.42***
	(1.61)	(1.60)	(1.66)	(1.64)
Experiential	-4.14	-3.92	-8.81*	-8.43*
	(5.44)	(5.40)	(4.77)	(4.67)
Interactive	12.02***	12.44***	6.03*	6.17**
	(3.50)	(3.47)	(3.13)	(3.06)
Constant	102.2***	101.8***	122.7***	99.40***
	(4.12)	(4.06)	(3.98)	(16.40)
Observations	1,114	1,114	1,114	1,114
Adjusted R-squared	0.04	0.08	0.36	0.40

Unstandardized betas, Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

To sum up, by taking the differences between modules, LD activities were strong predictors of the average time spent on VLE platform. In particular, students spent less time on VLE if they were required to do more productive and experiential activities while the opposite is true when they engaged in communication and interactive learning activities.

5. DISCUSSION

5.1 Implications

Firstly, our longitudinal visualization at a static level of LD suggested that teachers designed learning activities differently over time. In line with our previous work [45, 48], assimilative and assessment activities accounted for the majority of learning activities followed by productive activities, whereas experiential, interactive, communication, and finding information were less common. In line with basic principles of LD, more assimilative activities were employed at the beginning of the course: students were required to acquire and obtain new knowledge and information about a particular module, such as reading course syllabus, watching the introductory lecture, and so forth. Towards the end of a module, fewer assimilative activities were used, whereas more formative and summative assessments were made to evaluate the understanding of learners [6]. Multiple peaks in assessment activities also indicated that the learning process was continuously assessed over time, rather than relying solely on a large final exam. Continuous formative and summative assessment plays a very important role in distance courses, since small and constant assessments can both motivate learners and provide an accurate evaluation of their understanding over time, in order to intervene in time [46].

Secondly, our dynamic inspection on the LD of each module over time revealed that the use of LD varied considerably across modules and disciplines. A balanced approach of LD can be seen in module 2 in the Business and Law faculty, in which it consists of six out of seven LDs with equally distributed workloads for each activity and each week. When there was an assessment, the workload on other activities were reduced to avoid the overwhelming workload on students (see Figure 4). This is a very important remark for teachers and course designers since learners can be sensitive to peaks and troughs in workload, which in turn may damage their learning experience. Such example could be observed in module 1 in Art and Social Science discipline, in which there was a huge surge in the workload in week 10, which was more than 20 hours for all learning activities, compared with the average of 9 hours per week. Another example of a potentially unbalanced design was module 3 in the Faculty of Education and Language studies, which only used three types of LD throughout the course (i.e., assimilative, assessment, and productive). Evidently, we do not judge which design is good or bad, but this dynamic visualization of LD across modules can help educators reflect on their LD to anticipate whether their design best serves the learning objectives and learner experience.

Thirdly, using social network analysis we were able to observe how different learning activities were connected to each other. Our results suggested that if we concentrate on a single component of learning design in isolation, we might omit the complexity and critical features of the instructional dynamic. By adopting the view of system of practice [21], our empirical evidence strengthened the view of Hora and Ferrare [24] which indicated that teachers perceive certain learning activities as being meant for each other (i.e. assimilative & productive, communication & experiential) and these perceptions varies across disciplines. Interestingly, even though certain disciplines exhibited favorable practice towards a particular learning activity, each module utilized it with other learning activities in different ways. For example, it is apparent that assimilative activities were the most common learning activities in all three exemplar modules. However, the repertoire of practice in module 1 (assimilative, information, and productive) was different from module 2's (assimilative, information, communication, experiential, and productive) and module 3's (assimilative, assessment, and productive). Overall, learning activities are best viewed in relation to one another in multiple dimensions throughout time.

Our final takeaway is by taking into account the context of learning across 38 modules, learning designs were strong predictors of the time spent on VLE platform. Even though significant effects of certain learning activities on VLE activities were identified in our analysis, we advise readers to interpret them with cautions. As discussed above, learning activities should be perceived in relation with one another rather than in isolation. For example, our results showed that students spent less time on VLE when they engaged in productive activities. However, this did not imply that by simply cutting down productive activities, students will be more likely to engage. It is because each module employed productive activities in relation with different learning activities in different ways at different points in time. Students who engaged in productive activities which include building, constructing, and creating a 'knowledge nugget' may work offline. If they are required to share these 'knowledge nuggets' with other students then a rise in communication activities is expected as they post their thoughts and creations to the discussion forum.

From a researcher's perspective, by acknowledging the distinctive features of each discipline, we can considerably increase the accuracy of predicting student engagement in VLE. From a practitioner's point of view, our results highlighted the need to appropriately balance learning design that fit with specific learning outcomes and disciplinary practice.

5.2 Limitations

First, the measurements of the average time spent on VLE were crude indicators. Capturing the time spent on actual learning activities while control for which VLE activities are dedicated to which learning activities, and other unobservable non-studying activities is difficult. This problem has also been addressed in LAK15 in which Joksimović, Gašević, Loughin, Kovanović and Hatala [26] confirmed that the choice of the time-on-task estimations (assignment, reading, discussion, adding a post, or updating post) played an important role in the overall model fit and subsequent model interpretation.

Second, in a time-series model, time lag issue may occur [12]. For example, students who anticipated an assessment in week 10 would start preparing in week 9. Thus, assessment should be discounted one week in order to accurately reflect its effect on VLE activities. However, determining time lag is challenging given the variances of LD and the inconsistencies across modules.

Third, the LD taxonomy has certain limitations. On one hand, it could be over-simplify the actual LD since there are sub-categories in each types of learning activities (i.e. there are many kinds of assessment such as tutor-marked assessment, and computer-based assessment). On the other hand, some learning activities are overlap between different categories (i.e. watching a lecture while replying to the chat could be both assimilative and communication).

Finally, at the time this paper was written, the OU does not model learning designs across a programme or curriculum perspective. Therefore, we are limited to what we can actually conceptually define and empirically test LD at a program level.

6. CONCLUSION AND FUTURE WORK

This study investigated how learning designs are configured over time and its effect on student activities in VLE by analyzing 38 modules over 30 weeks at the Open University UK. By visualizing how learning design changed over time, teachers can explicitly reflect on their practice as well as compare and contrast with others. Using social network analysis, we illustrated how different learning activities interact with each other and which repertoire of practice was frequently adopted. Our results indicated a wide variance in the number of learning activities was used as well as the workload balance across modules. When the workload is unbalanced according to the OULDI framework, teachers can anticipate potential problems in their design to make informed interventions.

Moreover, our panel data analysis on the effect of learning designs on VLE activities indicated that by controlling for the differences across modules, learning designs proved to be strong indicators of student activities. In particular, communication and interactive activities had a positive effect on VLE engagement whereas productive and experiential were associated with lower levels of VLE activities. Our findings reinforced and provided new empirical evidence of the importance of understanding pedagogical context in LA in order to translate the findings to sensible actions.

Our research contributes to the existing literature in LA & LD by providing visualizations of elements of LD, and empirically examining the actual student learning behaviors in relation with the teachers' pedagogical intentions. By analyzing the actual learning behaviors of students across a large number of online modules, our work addressed the issue of ecological validity of experimental studies in LD while enhanced the external validity of the findings. By connecting the LD (input) with students' learning behaviors (progress), our work also supports previous LA findings which were mainly based on students' learning behavior (progress) and learning outcomes (output).

Future scholars are recommended to consider the inter-relationships between learning activities in doing research on. For instance, social network metrics of LD can be incorporated in the prediction models. When more fine-grained data (i.e. how much time students are expected to spend on writing essays, watching video, listening to audio, etc.) become available, researchers can unfold the complexity of LD in a more specific manner. Multi-level analysis can be conducted on a large scale study to account for the heterogeneity across faculties, levels of study, modules, and configurations of learning design.

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