"Scaling up" learning design: impact of learning design activities on LMS behavior and performance

Bart Rienties
Open University,
Institute of Educational Technology,
Milton Keynes, UK.
00-44-1908332671
Bart.Rienties@open.ac.uk

Lisette Toetenel
Open University,
Institute of Educational Technology,
Milton Keynes, UK.
00-44-1908332809
Lisette.Toetenel@open.ac.uk

Annie Bryan
Open University,
Institute of Educational Technology,
Milton Keynes, UK.
00-44-1908332696
Annie.Bryan@open.ac.uk

ABSTRACT

While substantial progress has been made in terms of predictive modeling in the Learning Analytics Knowledge (LAK) community, one element that is often ignored is the role of learning design. Learning design establishes the objectives and pedagogical plans which can be evaluated against the outcomes captured through learning analytics. However, no empirical study is available linking learning designs of a substantial number of courses with usage of Learning Management Systems (LMS) and learning performance. Using cluster- and correlation analyses, in this study we compared how 87 modules were designed, and how this impacted (static and dynamic) LMS behavior and learning performance. Our findings indicate that academics seem to design modules with an "invisible" blueprint in their mind. Our cluster analyses yielded four distinctive learning design patterns: constructivist, assessment-driven, balanced-variety and social constructivist modules. More importantly, learning design activities strongly influenced how students were engaging online. Finally, learning design activities seem to have an impact on learning performance, in particular when modules rely on assimilative activities. Our findings indicate that learning analytics researchers need to be aware of the impact of learning design on LMS data over time, and subsequent academic performance.

General Terms

Measurement, Performance, Design.

Keywords

Learning design, Learning analytics, Academic retention.

1. INTRODUCTION

Learning analytics provide institutions with opportunities to support student progression and to enable personalized, rich learning [1-3]. With the increased availability of large datasets, powerful analytics engines [2], and skillfully designed visualizations of analytics results [4], institutions may be able to draw on past experience to create supportive, insightful models of primary (and perhaps real-time) learning processes [5].

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While substantial progress has been made in terms of predictive modeling in the Learning Analytics Knowledge (LAK) community over the last three to four years [2], one element that seems to be ignored is learning design.

Conole [6, p121] describes *learning design* 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". Learning design is widely studied in the Higher Education sector, but no study has yet empirically connected learning designs of a substantial number of courses with learning behavior in Learning Management Systems (LMSs) and learning performance. This study will begin to overcome this gap in learning analytics research by combining three different sources of data (i.e., data pertaining to learning design, LMS, and learning performance) from 40 blended and online modules involving a total of 21,803 learners. In so doing, it will enable LAK researchers to better understand which learning design elements may be important for enhancing learning processes and performance.

1.1 Learning design taxonomy

The learning design taxonomy used for this process was developed as a result of the Jisc-sponsored Open University Learning Design Initiative (OULDI) [7], and was developed over five years in consultation with eight Higher Education institutions. Learning design as described by Conole [6] is process based: practitioners make informed design decisions with a pedagogical focus and communicate these to their colleagues and learners. This is especially relevant for institutions which deliver distance learning, such as the Open University UK (OU). At the OU, modules are designed by teams of academics based in a central location, but delivered to learners by different tutors in a wide range of locations.

Table 1 shows the learning design taxonomy, which identifies seven types of learning activity. *Assimilative activities* relate to tasks in which learners attend to discipline specific information. These include reading text (online or offline), watching videos, or listening to an audio file. By *finding and handling information*, for example on the internet or in a spreadsheet, learners take responsibility for extending their learning, and are therefore engaged in active learning [8]. *Communicative activities* refer to any activities in which students communicate with another person about module content. *Productive activities* draw upon constructionist models of learning, whereby recent research has indicated that learners who build [9] and co-construct new artefacts learn effectively [10]. *Experimental activities* develop 'students' intrinsic motivation and industry-relevant skill transfer' [11, p211] by providing learners with the opportunity to apply their learning in a real life setting. *Interactive activities* endeavor to do the same, but in some fields this is not possible: for example, in medicine, such activities would have health and safety implications for either the learner or the person that they interact with. In these situations, a simulated environment might be appropriate so that learners can apply their learning to a realistic setting [12]. Finally, *assessment activities* encompass all learning materials focused on assessment, whether enabling teaching staff to monitor progress (formative); 'traditional assessment for measurement purposes' [13, p182] (summative); or activities that allow learners to benchmark against their own or fellow learner's performance (ipsative).

Table 1. Learning design activities

	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.

2. Method

2.1 Setting

This study took place at the OU, the largest higher education provider of online distance education in Europe. A process of "module mapping" (i.e. analyzing and providing visualizations of the learning activities and resources involved in a module) was introduced as part of a university-wide learning initiative [14] which aims to use learning design data for quality enhancement. The mapping process is an intensive one, typically taking between one and three days for a single module, depending on the module's number of credits, structure, and quantity of learning resources. A team of learning design specialists reviewed all the available learning materials, classifies the types of activity, and quantifies the time that students are expected to spend on each activity.

Classifying learner activity can be subjective, and consistency is important when using the data to compare module designs across the univeristy. Therefore, the learning design team held regular meetings to improve consistency across team members in the mapping process. Once the mapping process was complete, the learning design team manager reviewed the module before the findings were sent to the faculty. Academics had the opportunity to comment on the data before the status of the design was finalised. In other words, each mapping was at least reviewed by three people, which enhanced the reliability and robustness of the data relating to each learning design.

2.2 Instruments

2.2.1 Learning Design mapping

The learning design tool at the Open Universtiy is a combination of graphical, text-based tools that are used in conjunction with learning design activities, which were mandated at particular times in the design process. In total 87 modules were mapped by the learning design team in the period January-August 2014. For each module, the learning outcomes specified by the module team (pertaining to knowledge and understanding; cognitive skills; key skills; practical and/of professional skills) were captured by the learning design specialist. Each activity within the module's weeks, topics, or blocks was categorised according to the learning design taxonomy (see Table 1). These categorisations were captured in an "activity planner" (or "blueprint").

2.2.2 LMS Data

In line with Tempelaar et al. [3], two different types of LMS data in Moodle were gathered per module in a static and dynamic manner: total number of visits to the LMS; and average time spent on LMS. Subsequent derivatives of these two types of data per week were recorded for week -2 until week 40 (data streams starts two weeks before the actual start of the module). Although more fine-grained learning analytics tracking data were available on types of content, materials and ICT tools (e.g., wikis, videoconference, discussion forums), given the diversity in usage and the fact that not all modules used all the ICT tools we measured, we focused on aggregate user statistics per week across the LMS., Such data was available for 32 modules at the time this study was conducted.

2.2.3 Learning performance

Learning performance was calculated by the number of learners who completed and passed the module relative to the number of learners who registered for each module. The academic retention ranged between 28.57% and 100%. These figures do need to be read in the context of the OU's mission to provide education for all, regardless of entrance requirements [15].

2.2.4 Data analysis

As a first step, we analyzed the underlying structures and collective patterns of the seven learning design activities by using cluster analysis of the 87 modules. In line with the recommendations of Hair, Tatham, Anderson and Black [16], we conducted three different types of cluster analyses (K-means, hierarchical ward, hierarchical furthest distance). Given that the results were similar in terms of assigned clusters, in the results section we will report cluster results using K-means analysis, as this method is most commonly used. We then tested solutions for 2-5 clusters using K-means cluster analyses. The results seemed to indicate that four clusters fitted the data best (at 5 clusters, too few meaningful clusters were left). We labelled the clusters using theoretical concepts [6, 7, 17-19] and in-depth experience of learning design team.

As a second step, we merged the learning design data with the LMS and learner retention data based upon module ID and year of implementation. A mix of 15, 30 and 60 credit modules was present. 32 modules could be linked with LMS learning behavior, and 40 with learning performance data. Such data were not yet available for 23 running modules, as these are currently being undertaken by learners, while 8 modules (primarily MOOCs) were not included in standard OU registration processes. For 8 modules the LMS data was not released yet. Finally, 16 module learning designs referred to future designs for the academic year

2015-2016. Follow-up ANOVA and correlation analyses were conducted using SPSS 21.

3. Results

3.1 Cluster analysis of learning designs

We conducted a K-means cluster analysis to identify common patterns in how the 87 module teams designed and balanced the seven learning design activities.

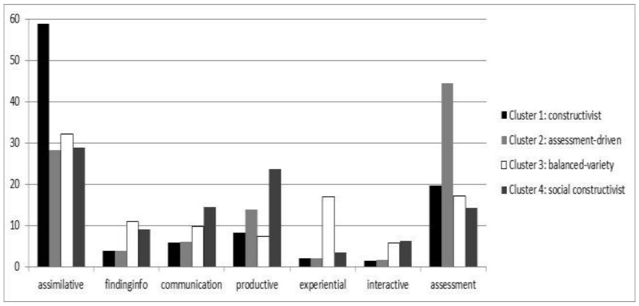

Figure 1 Cluster analysis of learning design

As illustrated in Figure 1, Cluster 1 modules seemed to have a strong emphasis on assimilative activities, as 58% (SD = 11%) of learning activities fell into this category, Students undertook assimilative activities such as reading module materials, watching videos and YouTube materials, reviewing core concepts and approaches. In comparison to other modules, Cluster 1 modules had a lower focus on the other six learning design activities. 24 (28%) modules were assigned to Cluster 1, which we label as *constructivist modules*. For example, a first-year science introductory module focused on understanding principles and concepts in a range of topics, with several online assessments to test (individual) learners' understanding. Please note that not all modules in Cluster 1 fit this description, but in comparison to other clusters modules in Cluster 1 tended to have a relatively stronger focus on cognition and understanding (in terms of the taxonomy proposed by [20]). 22 (25%) modules were positioned in Cluster 2, with a strong focus on assessment (M = 44.54, SD = 12.05), such as formative assessment for learning (e.g. write, present, report, demonstrate) and summative assessment of learning [3, 21]. In comparison to other modules, those in Cluster 2 had a relatively limited focus on assimilative, communication, and interactive learning design activities. For example, an introductory history course focused on providing a historical perspective of a particular region in the UK, whereby a range of assessment tasks were provided focused on culture, society and nationhood. We label Cluster 2 as *assessment-driven*.

The 24 (28%) modules in Cluster 3 had a more or less equal balance between assimilative and assessment learning design activities, with a relatively high focus on experiential activities. For example, the health and social care module used a mix of understanding basic concepts as well as applying these concepts using case-studies, self-reflections and collaborative approaches. Therefore, we label Cluster 3 modules as *balanced-variety*, whereby a range of different activities were expected from learners.

Finally, the 16 (18%) modules in Cluster 4 seemed to use more a learner-centered learning design approach, whereby relatively more time was devoted towards communication, productive and interactive activities. For example, in a foreign language module, a range cognitive, skills-based, reflective and application tasks are assessed using a mix of technology tools and blended tuition. Therefore, we label these Cluster 4 modules as *social constructivist*.

3.2 Linking learning design activities

Separate Pearson correlation analyses between the seven learning design activities, total workload, and level of study indicated that several groups of learning design activities were interrelated. Workload is 'the number of hours that students objectively spend on studying' [22, p684]. In this study, workload was calculated by the learning design team as part of the module mapping process. Workload has 'been recognized as a major factor in the teaching and learning environment'[22, p684] and is of particular importance at the OU.

We found that assimilative activities were negatively related to all of the other six learning design activities, indicating that focusing more on cognition and content reduces the focus on other activities. No other statistically significant correlations were found. Similar to assimilative activities, assessment was negatively related to five of six learning design activities, which may indicate that module teams implicitly or explicitly make a trade-off between these learning design activities. Total workload was not significantly related to any of the learning design activities, indicating that teachers did not reserve any specific extra time for a particular learning activity. Finally, the level of the module (year 1, 2, 3, post-graduate) was positively correlated with communication and total workload. Using ANOVA, no significant differences were found with respect to disciplines. In other words, most disciplines used a range of learning design approaches, which seems contrast with previous findings of studies [23] highlighting that disciplinary context strongly influences the learning design.

3.3 Relating learning design with LMS behavior

We linked the learning designs of 32 modules followed by 19,322 learners with their LMS data. On a total of 2,186,246 occasions, the LMS was visited by 19,322 students. On average, students spent 122.71 minutes per week (SD=92.47, range 14.39-167.94) online during each of the first 10 weeks of the module. This wide range highlights strong underlying differences in the way modules were designed. Some modules primarily relied on traditional methods of distance learning and course delivery via books and readers, with limited interactions in the LMS [24]. Other modules provided most or all of their course materials, tasks and learning activities exclusively online and expected students to engage actively in the LMS during the week. As a result, LMS activity should only be regarded as a proxy for student engagement in formal online activities, as at this point in time the OU does not systematically collect data about formal or informal offline activities.

We visually analyzed whether the four clusters lead to different LMS usage over time. As illustrated in Figure 2, in particular in the first ten weeks significant differences (using ANOVAs, not illustrated) are present in terms of average time spent per week between Cluster 4 social constructivist modules and the other modules. Please note that for Cluster 3 LMS data for was only available for one module.

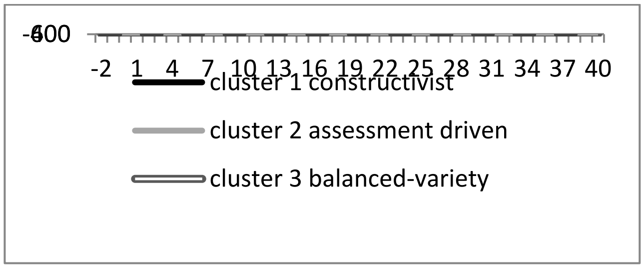

Figure 2 Average LMS usage across four clusters

LMS visits were positively related to communication activities and total (planned) workload, and negatively related to assessment activities. Average time spent in the LMS correlated positively with finding and handling information activities, communication activities, and total workload, whilst, again, a negative relation was found with assessment activities. Finally, if we split the average time spent in the LMS for week -2 till week 10, only communicative activities at week 0 and workload were significantly correlated. Average time spent during weeks 1-10 were strongly related to modules with substantial learning activities in terms of finding and handling information, and communication. In other words, the learning design decisions of teachers seemed to strongly influence how students were engaging with the LMS, in particular when more inquiry- or social constructivist learning activities were included in the learning design.

3.4 Relating learning design with learning performance

As a final step, we linked the learning design metrics with learning performance, as illustrated in Table 2. The only significant (negative) correlations between the seven learning design activities and learning performance were with assimilative activities. Modules with a relatively high proportion of assimilative learning activities had significantly lower completion and pass rates than other modules. Furthermore, positive correlations were found between productive and assessment activities and pass rates, although these were not

statistically significant.

	Assimi-lative	Finding information	Communi-cation	Productive	Exper-iential	Inter-active	Assess-ment	total
Registrations	.286	-.027	-.196	.088	-.174	.032	-.203	-.022
Completed of Registered Starts	-.302	.046	.048	.269	-.018	-.178	.174	-.223
Passed of Completed	-.326*	.044	.017	.138	.159	.029	.148	-.262
Passed of Registered Starts	-.331*	.043	.035	.261	.037	-.136	.177	-.263

n = 40, * p < .05.

Table 2 Linking learning design with learning performance

No significant correlations were found between our LMS indicators and learning performance (not illustrated). Follow-up ANOVA analyses indicated no significant differences in learning performance between the four clusters. In other words, although there are substantial variations in the 40 module designs, our findings indicated that applying one of the four design templates did not necessarily disadvantage learners in terms of retention. However, extensive reliance on assimilative activities did seem to have a negative influence on learning performance, although given the relatively small number of modules within the sample we caution readers against overgeneralization.

4. Discussion

Pedagogy and learning design have played a key role in computer-assisted learning in the last two decades [6, 19, 25], but research has not extensively linked learning design to learning behavior and learner performance [23, 26]. Progress has recently been made in how (combinations of) individual learning design elements (e.g., task design, feedback, scaffolding, structure) influence learning processes and success in experimental and natural settings within single modules. However, this study was the first to link a large range of learning designs from multiple blended and online modules with learning behavior in a Learning Management System (LMS) and learning performance data.

The study’s first important finding is that academics seem to design modules with an “invisible” blueprint in their mind. Our cluster analyses yielded four distinctive learning design patterns as shown in Figure 2, namely constructivist, assessment-driven, balanced-variety, and social constructivist modules. This means that whilst the learning design process intends to stimulate creativity, upon analysis these ‘unique’ designs neatly fitted into four broad theoretical perspectives. This finding suggests that although creativity is still present in the process (as none of the designs are identical), academic staff do employ similar combinations of pedagogical underpinnings into their learning designs [23, 26].

Our second and perhaps most important finding is that learning design and learning design activities in particular strongly influence how students are engaging in our LMS. Particularly in social constructivist environments, students actively engage with the LMS, while in constructivist and assessment-based modules, online activity seems substantially lower. While a vast body of research in computer supported collaborative learning (CSCL) [25] has found that learning design influences how people learn, in learning analytics research learning design seems to be mostly ignored, or overlooked. Without mapping and linking the planned learning design activities (e.g., assessments, interactive, or communication activities) with LMS usage, learning analytics researchers might find it difficult to explain why certain peaks and troughs occur over time.

Our third finding is that learning design seems to have an impact on learning performance. In particular, modules with a heavy reliance on content and cognition (assimilative activities) seemed to lead to lower completion and pass rates. The availability of learning analytics data means that management and course teams often review courses whilst they are still in progress. If this data suggests that learners do not perform according to the initial learning design, it is tempting to take action. Often this includes providing additional material to learners in the form of reading lists or additional handouts. As this study found that modules with a strong reliance on assimilative activities did seem to have a negative influence on learning performance, it suggests that such interventions might make matters worse.

5. Conclusions and future work

A substantial limitation of this study is the relatively small linked sample size. Although the OU learning design team mapped a substantial amount of 87 modules, only 32 modules containing LMS data and 40 modules containing learning performance data could currently be linked due to module completion timescales. As a result, more advanced regression or structural equation modeling were not feasible to determine the direct and indirect relations in our three datasets. In the near future, we would be able to extend the sample when more data becomes available in order to better understand the complex (inter)relations of learning design on learning processes and outcomes.

Combining this analysis with the learning outcomes data allows sharing of ‘good practice’ based upon robust analysis. Furthermore, a particularly useful feature would be to integrate this with demographic, individual and socio-cultural data about students, which may influence whether a learning design is suitable for a range of learners. In terms of practical implications for LAK, researchers, teachers and policy makers need to be aware of how learning design choices made by teachers influence subsequent learning processes and learning performance over time. Following Arbaugh [17], there is an urgent need for researchers and managers to combine research data and institutional data and work together in order to unpack how context, learner characteristics, modular and institutional learning design activities impact the learning journeys of our students.

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