The impact of 151 learning designs on student satisfaction and performance: social learning (analytics) matters

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ABSTRACT
An increasing number of researchers are taking learning design into consideration when predicting learning behavior and outcomes across different modules. This study builds on preliminary learning design work that was presented at LAK2015 by the Open University UK. In this study we linked 151 modules and 111.256 students with students' satisfaction and performance using multiple regression models. Our findings strongly indicate the importance of learning design in predicting and understanding performance of students in blended and online environments. In line with proponents of social learning analytics, our primary predictor for academic retention was the amount of communication activities, controlling for various institutional and disciplinary factors. Where possible, appropriate communication tasks that align with the learning objectives of the course may be a way forward to enhance academic retention.

CCS Concepts
• **Applied computing~Distance learning**
• **Applied computing~E-learning**

Keywords
Data analytics, Collaborative Learning, Distance Learning

1. INTRODUCTION
There is an increased interest in predictive modeling in education. Beyond identifying students that require additional support, in the Learning Analytics Knowledge (LAK) community many scholars are interested in identify trends in learning and teaching from rich data sources. In order to identify the meaning of some of these trends, pedagogical information is required and this has often been ignored to date [1]. Pedagogical knowledge or information granted through Learning Design provides the context to the quantitative analysis that Learning Analytics is able to provide. Although several studies [2-4] and a specific LAK workshop [5] on learning design have used principles of learning design to unpack the complexities of learning analytics in the last four to five years, few studies have empirically compared the impact of different learning designs on learning processes and outcomes. For example, 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 the definition of this concept has various meanings in different settings and 'similar work has been carried out under such names as pedagogical patterns, learning patterns and pattern language' [3, p1441].

Learning design is implemented as a way to improve course design [4, 7, 8], but few studies have empirically connected learning designs of a substantial number of courses with learning behavior in Learning Management Systems (LMSs) and learning performance. This study builds on preliminary learning design work that was presented at LAK2015 by the Open University UK (OU). In this explorative study we indeed found that learning design decisions made by teachers were related to learning behavior of students in blended and online environments [9]. An important finding of this study amongst 40 modules and 27K students was that assimilative learning design activities (such as reading, watching) were positively correlated to learner satisfaction, but negatively to academic performance. Our current study builds on this initial explorative study by focusing on an extensive elaboration of the scope and reach of our data analysis, whereby we linked 151 modules and 111K students with students' satisfaction and performance using multiple regression models, whereby we were able to control for various institutional and disciplinary factors to determine what the key drivers for learning are, and whether our initial findings still hold with this richer dataset.

1.1 Learning design meets learning analytics
While substantial progress has been made in the last 10 years in conceptualising learning design [7, 8] by for instance using a data-informed approach, relatively few studies have investigated how educators in practice are actually planning, designing, implementing and evaluating their learning design decisions. Evaluating the success of a learning activity for instance by analysing activity logs of student behavior is more informative when compared to the overall pedagogy and design of the course.

By linking large datasets across a range of 40+ modules in online and blended learning settings, both studies [9] point to the important notion often ignored in learning analytics: by analysing the impact of learning design on learner satisfaction and academic performance across a range of modules, a cross-sectional study may provide crucial (generalizable) insights beyond the specific research findings within a single module or discipline.

In a recent study by Li, Marsh and Rienties [10], using logistical regression modelling learner satisfaction data were analysed and the findings indicated that these proxies of learning design had a

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strong and significant impact on overall satisfaction. Similarly, using logistic regression with a primary purpose of improving aggregate student number forecasts¸ Calvert [11] found 30 variables in five broad categorizations which broadly predicted progression of students..

Although these studies provide (indirect) evidence that proxies of learning design and individual student characteristics influence learner satisfaction and academic retention, none of these studies have identified across a large range of modules whether objectively mapped learning designs of modules have an impact of actual student behavior, learner satisfaction and academic retention. In this follow-up study of our LAK 2015 paper, we aim to address this gap by comparing the learning designs of 151 modules that were followed by over 110k online students at different disciplines, levels, and programmes.

2. METHOD

2.1 OULDI Learning Design

The learning design taxonomy used for this article was developed as a result of the Jisc-sponsored Open University Learning Design Initiative (OULDI) [12], and was developed over five years in consultation with eight Higher Education institutions. In contrast to instructional design, Learning Design is process based [6]; 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. The OU follows a collaborative design approach, based upon almost a decade of academic and institutional research ([13].

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.

For a detailed description of the seven learning descriptions and theoretical foundations, we refer to previous published work [9, 14]. *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. In terms of social learning analytics conceptualisations, the next five categories describe different options available to teachers to create an interactive, social learning environment [1, 15]. 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. *Communicative activities* refer to any activities in which students communicate with another person about module content. *Productive activities* refer to activities whereby learners build and co-construct new artefacts. *Experimental activities* provide learners with the opportunity to apply their learning in a real life setting. *Interactive activities* endeavor to do the same, such as simulations. Finally, *assessment activities* encompass all learning materials focused on assessment to monitor (formative) progress and/or traditional assessment for measurement purposes. Table 1 identifies the seven types of learning activity in the OULDI model.

2.2 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 [9, 14] which aims to use learning design data for quality enhancement. The mapping process is comprehensive, but labour intensive; 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 disciplines in the institution. 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.

2.3 Instruments

2.3.1 Learning Design mapping

The learning design tool at the OU is a combination of graphical, text-based tools that are used in conjunction with learning design workshop activities, which were mandated at particular times in the design process. In total 189 modules were mapped by the learning design team in the period January 2014-October 2015. Given that the OU offers multiple presentations of modules per year, in total 276 module implementations were recorded, of which we could link 151 modules with learning performance data (see next section). In total 113.725 students were enrolled in these 151 modules, with an average module size of 753.15 (SD= 828.89). For each module, the learning outcomes were captured in the Learning Design tools. Each activity within the module’s weeks, topics, or blocks was categorized according to the learning design taxonomy (see Table 1). These categorizations were captured in a visual representation in the form of an “activity planner” (or “blueprint”).

2.3.2 *Learner satisfaction*

Our second core dependent variable is learner satisfaction. In the past thirty years, the OU has consistently collected learner feedback to further improve the learning experience and learning designs. In line with other learner satisfaction instruments [16-18], at the OU the Student Experience on a Module (SEaM) questionnaire was implemented. The SEaM institutional survey was introduced in 2012/13 combining two previous surveys using a census approach; so inviting all learners on all modules to participate. It consists of three themed sets of in total 40 questions: 1) The module overall (10 items), 2) Teaching, learning and assessment (14 items) and 3) Feedback on the tutor (16 items). Following our analysis of key drivers amongst 65K students' learning experience [10], for this analysis we used the aggregate scores of five core items that drive learner satisfaction.

2.3.3 *Academic retention*

Our first dependent variable is academic retention, which was calculated by the number of learners who completed and passed the module relative to the number of learners who registered for each module. Academic retention is a key concern of many institutions, and in particular at the OU. The academic retention ranged between 34.46% and 100%, with an average of 69.35 (SD= 12.75). These figures do need to be read in the context of the OU's mission to provide education for all, regardless of entrance requirements [19].

2.3.4 *Institutional analytics data*

In line with previous studies [20-22], we included several institutional analytics data that are known to influence the students' learning experience, such as the level of the course (ranging from level 1 to level 4, which is roughly translated into year 1 to post-graduate) [11], the specific discipline [23], the year of implementation, size of the class or module [20-22]. In terms of VLE engagement, the average number of minutes spent in the VLE per week were used as proxy for engagement [24].

2.4 Data analysis

All data were collected on an aggregate, module level. As a first step, we merged the learning design data with the LMS and learner retention data based upon module ID and year of implementation. In total 151 module implementations could be linked with LMS learning behavior and learning performance data. In order to correct for any selection-bias in terms of selecting modules for these mapping activities, we compared these 151 module implementations vs. 1016 module implementations which were not mapped in the Learning Design tool in 2014/2015. Indeed significantly more level 0-1 and fewer post-graduate modules were mapped, but no significant differences were found in terms of academic performance or student experience (so limiting selection bias). As the learning design team primarily focused on large scale undergraduate modules, this result was expected.

All data was anonymized by the first author, whereby names and codes of modules and respective disciplines were replaced by random codes to safeguard the identities of teachers and their respective faculty. Follow-up regression analyses were conducted using SPSS 21.

3. RESULTS

3.1 Relating learning design with learner satisfaction

As a next step, we linked the learning design metrics with learner satisfaction. On average, 80.85% (SD= 11.06) of the 26483 (28.99%) students who responded to the SEAM survey were satisfied with their learning experience, with a range of 39-97%. A significant positive correlation was found between assimilative activities and Average SEAM ($r = .333$, $p < .01$), while negative correlations were found in terms of finding information ($r = -.258$, $p < .01$) and communication ($r = -.224$, $p < .01$).

Three separate regression analyses were conducted, whereby learner satisfaction was significantly predicted by students who followed the Level 0 access models, whom were significantly more positive than other modules. Other institutional variables such as disciplinary differences were mostly not significantly predicting learner satisfaction, in line with previous findings [10] that students at the OU have similar learning experiences irrespective of disciplinary differences.

Table 2: Regression model of learner satisfaction and learning performance predicted by institutional and learning design analytics

	Learning Satisfaction	Learning performance
Level0	.351**	.005
Level1	.265	.017
Level2	-.212	-.004
Level3	-.018	.215
Year of implementation	-.059	-.151*
Faculty 1	.213*	.360**
Faculty 2	.045	-.189*
Faculty 3	.236*	.069
Faculty other	.051	.034
Size of module	-.071	-.239**
Finding information	-.294**	-.154
Communication	.050	.500**
Productive	-.274**	.133
Experiential	-.105	.008
Interactive	.221*	-.049
Assessment	-.221*	.063
LMS engagement	.117	-.190*
Learning Satisfaction		-.058
R-sq adj	31%	36%

n = 150 (Model 1-2), 140 (Model 3), * $p < .05$, ** $p < .01$

When we added the learning design activities, learner satisfaction was significantly negatively predicted by finding information, experiential and assessment learning activities, and positively predicted by interactive activities (again with assimilative activities as the reference point). Separate analysis with assessment as reference point (not illustrated) indicated that assimilative activities significantly and positively predicted learner satisfaction, while the betas for the other three predicting learning activities remained similar. Finally, when we added LMS engagement the primary predictors remained the same, but engagement in LMS did not predict learner satisfaction. The seven learning activities explained 18% of variance, and when the institutional analytics were included 12% of unique variance was explained. The final, complete model is presented in Table 2. In other words, learning design activities had a significant and substantial impact on learner experience, whereby modules with more assimilative and fewer inquiry and discovery-based learning activities were perceived to lead to better learner experiences (for at least those who complete the surveys).

3.2 Relating learning design with learning performance

Three regression models were used to predicted academic retention, whereby the final model is presented in Table 2. Academic retention was significantly positively predicted by students following Faculty 1 (relative to reference point of Faculty 4). Furthermore, academic retention was negatively predicted by the overall size of the module and year of implementation. In other words, modules that were relatively large in size, more focused on natural sciences, and those that were taught in more recent academic years 2014-2015 had relatively lower retention rates than smaller modules and modules taught in academic years 2012-2013. When adding the average learning experience and VLE engagement, no significant relations were found between learner satisfaction, VLE engagement and academic retention. Finally, when adding the seven learning design activities, communication significantly and positively predicted academic retention. LMS engagement negatively predicted academic retention when the seven learning design activities were included, which may counterbalance some of the effects of communication. The seven learning activities explained 11% of variance, and when the institutional analytics were included 6% of unique variance was explained. Separate analyses (not illustrated) with assessment rather than assimilative learning design activities as a reference point indicated that assimilative had a negative but non-significant impact on retention when taking the other variables into account. In other words, as illustrated in Figure 1 in simple laymen terms, communication (as reported in percentages on Y-axis) seemed to be a key lever for retention (as reported from 0-1 on X-axis) in blended and online distance education at the OU.

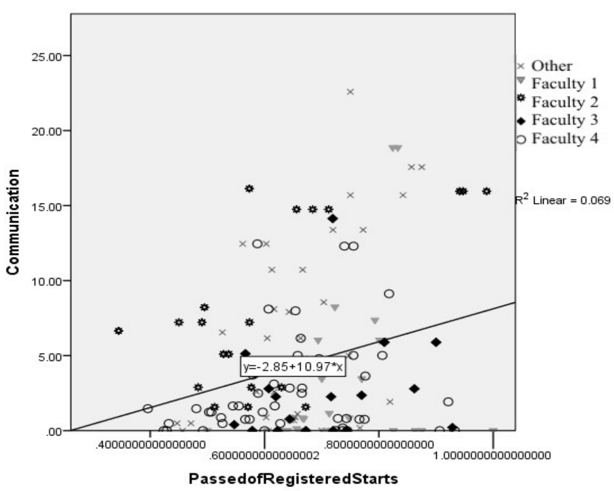

Figure 1: Communication and academic retention (per discipline).

4. DISCUSSION

Pedagogy and learning design have played a key role in computer-assisted learning in the last two decades [6], but research has not extensively linked learning design to learner performance [23, 25]. 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. Building on our first study [9], this study has provided strong empirical evidence that learning design had a significant influence on learner satisfaction and academic retention amongst 151 modules followed by 113.725 students.

Our first and perhaps most important finding is that learning design and learning design activities in particular strongly influenced academic retention. A major innovation is that we were able to move beyond simple correlation analyses to multiple regression analyses, whereby we were able to control for common institutional analytics factors and disciplinary differences. This approach was useful, as our initial analysis with correlation analysis presented at LAK2015 seemed to indicate that modules with a heavy reliance on content and cognition (assimilative activities) seemed to lead to lower completion and pass rates. However, when controlling for the institutional data sources and modelling the seven learning design activities simultaneously, the negative link between assimilative learning design and academic retention was no longer significant. The primary predictor of academic retention was the relative amount of communication activities. This is an important finding as most teachers are the OU and across the globe have a tendency to focus on cognition rather than social learning activities [21, 23, 26], while recently several authors in the LAK field have encouraged teachers and researchers to focus on the social elements of learning [1, 21].

Our second important finding was that learner satisfaction was strongly influenced by learning design. Modules with assimilative activities and fewer student-centred approaches like finding information activities received significantly higher evaluation scores. However, a crucial word of caution is in place here. Although we agree with others [17, 18, 21] that learner satisfaction and happiness of students is important, it is remarkable that learner satisfaction and academic retention were not even mildly related to each other in Table 2. More importantly, the (student-centred) learning design activities that had a negative effect on learner experience had a neutral to even positive effect on academic retention.

Two possible explanations are available for the widely different effects of learning design on learner satisfaction and academic retention. First, although more than 80% of learners were satisfied with their learning experience, as evidenced by several leading scholars [25, 26] learning does not always needs to be a nice, pleasant experience. Learning can be hard and difficult at times, and making mistakes, persistence, receiving good feedback and support are important factors for continued learning. Our findings indicate that students may not always be the best judge of their own learning experience and what help them in achieving the best outcome.

Second, on average 72% of students who participated in these 151 modules did not complete the learner satisfaction survey. In certain modules actual dropout was well above 50%, indicating that students were “voting with their feet” when the learning design and/or delivery did not meet their learning needs. An exclusive focus on learner satisfaction might distract institutions from understanding the true learning experiences and academic retention. If our findings are replicated in other contexts, a crucial debate with academics, students and managers needs to develop whether universities should focus on happy students and customers, or whether universities should design learning activities that stretch learners to their maximum abilities and ensuring that they eventually pass the module. Where possible, appropriate communication tasks that align with the learning objectives of the course may seem to be a way forward to enhance academic retention.

5. CONCLUSION AND FUTURE WORK

A major innovation in comparison to our initial study is that we were able to execute multiple regression analyses, whereby we were able to control for common institutional analytics factors and disciplinary differences, but it highly likely that additional factors contribute to the satisfaction and retention to the factors included in the model. In the near future, we would be able to extend this sample further when more data becomes available in order to better understand the complex (inter)relations of learning design on learning processes and outcomes as we will be able to combine this with further data sets such as student and tutor comments.

In addition, 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, so that subgroups can be analysed. This 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.

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