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The impact of learning design on student behaviour, satisfaction and performance: A cross-institutional comparison across 151 modules

Bart Rienties*, Lisette Toetenel**

Open University UK, Institute of Educational Technology, Milton Keynes, MK7 6AA, UK

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ABSTRACT

Pedagogically informed designs of learning are increasingly of interest to researchers in blended and online learning, as learning design is shown to have an impact on student behaviour and outcomes. Although learning design is widely studied, often these studies are individual courses or programmes and few empirical studies have connected learning designs of a substantial number of courses with learning behaviour. In this study we linked 151 modules and 111.256 students with students' behaviour (<400 million minutes of online behaviour), satisfaction and performance at the Open University UK using multiple regression models. Our findings strongly indicate the importance of learning design in predicting and understanding Virtual Learning Environment behaviour and performance of students in blended and online environments. In line with proponents of social learning theories, our primary predictor for academic retention was the time learners spent on communication activities, controlling for various institutional and disciplinary factors. Where possible, appropriate and well designed communication tasks that align with the learning objectives of the course may be a way forward to enhance academic retention.

1. Introduction

Over the past ten years, there is an increased interest in the use of institutional data to understand academic retention, including the use of predictive modelling following principles of Learning Analytics (LA). 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 (Conde & Hernández-García, 2015; Ferguson & Buckingham Shum, 2012; Gasevic, Rosé, Siemens, Wolff, & Zdrahal, 2014; Tempelaar, Rienties, & Giesbers, 2015). Pedagogical knowledge or information relating to Learning Design (LD) may provide a valuable context to advancing quantitative analysis for LA.

Conole (2012, 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". LD is focussed on 'what students do' as part of their learning, rather than the 'teaching' which is focussed on the content that will be delivered. Within this journal, there is an increased recognition that LD is an essential driver for learning (e.g, Giesbers, Rienties, Tempelaar, & Gijselaers, 2013; Hernández-Leo, Moreno, Chacón, & Blat, 2014; Moreno-Ger, Burgos, Martínez-Ortiz, Sierra, & Fernández-Manjón, 2008).

The focus of most LD research has been on conceptualising learning design principles (Armellini & Aiyegbayo, 2010; Hernández-Leo et al., 2014; MacLean & Scott, 2011), without focussing on what happens after the design process. To the best of our knowledge, only a few studies have investigated how educators in practice are actually planning and designing their course and whether this is then implemented as intended in the design phase. Hernández-Leo et al. (2014) analysed how 47 participants created 41 co-designed learning designs and found that LdShake was an appropriate platform to co-design innovative learning designs. In a review of 157 learning designs at the Open University UK (OU), Toetenel & Rienties (2016) found that educators mostly used assimilative activities (e.g., reading, writing, watching) and assessment activities in their learning designs. Completing the virtuous cycle of LD is essential in implementing and evaluating LD decisions in order to enhance the quality of learning.

* Corresponding author.
** Corresponding author.
E-mail address: bart.rienties@open.ac.uk (B. Rienties).

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Although LD is widely studied as a way to improve course design (Armellini & Aiyegbayo, 2010; Koedinger, Booth, & Klahr, 2013; MacLean & Scott, 2011), few institutions have captured and updated these data in order to reflect on how these courses are delivered to students. As a result, very few studies have been able to "connect" learning designs of a substantial number of courses with learning behaviour in Virtual Learning Environments (VLEs) and learning performance. In this study, we linked the learning designs of 151 modules and 111 K students with students' behaviour, satisfaction and performance at one of the largest providers of blended and online education, the Open University UK (OU). Our overall research question is to determine to what extent learning design decisions made by teachers predict VLE engagement, satisfaction and academic performance. We will first provide a brief overview of learning analytics, after which we will link learning design to learning analytics.

2. Learning analytics complements learning design

In the last five years, several authors have indicated that LA should take a social learning analytics perspective (Buckingham Shum & Ferguson, 2012; Ferguson & Buckingham Shum, 2012; Hickey, Kelley, & Shen, 2014). While in more traditional education/learning science disciplines the power of communication and collaboration is widely acknowledged (Arbaugh, 2014; Rosé et al., 2014; Vygotsky, 1978), most of the current practice in LA seemed to focus on predicting individual performance of students, and in particular students-at-risk.

A special issue on LA in *Computers in Human Behavior* (Conde & Hernández-García, 2015) indicated that simple LA metrics (e.g., number of clicks, number of downloads) may actually hamper the advancement of LA research. For example, using a longitudinal data analysis of over 120 variables from three different VLE systems and a range of motivational, emotions and learning styles indicators, Tempelaar et al. (2015) found that most of the 40 proxies of "simple" VLE LA metrics provided limited insights into the complexity of learning dynamics over time. On average, these clicking behaviour proxies were only able to explain around 10% of variation in academic performance. In contrast, learning motivations, emotions (attitudes), and learners' activities during continuous assessments (behaviour) significantly improved explained variance (up to 50%) and could provide an opportunity for teachers to help at-risk learners at a relatively early stage of their university studies. Although a large number of institutions are currently experimenting with LA approaches, few have done so in a structured way or at the scale like the OU, to which we now turn our attention.

In a recent study by Li, Marsh, & Rienties (2016), using logistical regression modelling learner satisfaction data of 62,986 learners in 401 undergraduate blended and online modules were analysed using 200 potential explanatory institutional, departmental and individual LA variables. In addition, several (crude) proxies of LD were included, such as number of assignments, duration of course, and workload. The findings indicated that these proxies of LD had a strong and significant impact on overall satisfaction, whereby learners who were more satisfied with the quality of teaching materials, assessment strategies, and workload were more satisfied with the overall learning experience. Furthermore, long-term goals of learners (i.e., qualifications and relevance of modules with learners' professional careers) were important predictors for learner satisfaction, in particular at post-graduate level. Individual learner characteristics were mostly insignificant, indicating that despite a wide diversity of learners studying at the OU the underlying learning experiences were similar. Similarly, using logistic regression with a primary purpose of improving aggregate student number forecasts, Calvert (2014) found 30 variables in five broad categorizations which broadly predicted progression of students: characteristics of the student, the student's study prior to the OU and their reasons for studying with the OU, the student's progress with previous OU study, the student's module registrations and progress and finally the characteristics of the module and qualification being studied.

In a recent important study measuring which factors predicted learner satisfaction and academic performance amongst 48 MBA online and blended learning modules in the US, Arbaugh (2014) found that learners' behaviour, as measured by social presence, predicted learner satisfaction and academic performance. Quite remarkably, the technological environment used in these 48 modules did not significantly predict learners' learning experience and performance. Therefore, Arbaugh (2014, p. 352) argued that "a resource-strapped business school may get the most 'bang for its buck' by allocating resources towards developing instructors when contemplating how best to support its online and blended offerings". In our own explorative study (Rienties, Toetenel, & Bryan, 2015), we found that LD decisions of 40 modules made by teachers were strongly related to learning behaviour of 27 K students in blended and online environments. Assimilative LD activities were positively correlated to learner satisfaction, but negatively to academic performance. In other words, even though students were more satisfied with modules that were knowledge focused, actual retention was negatively influenced by a strong focus on cognition.

In other words, by linking large datasets across a range of modules in online and blended learning settings (Arbaugh, 2014; Li et al., 2016; Rienties et al., 2015 ; Calvert, 2014), these studies point to the important notion often ignored in LA: by analysing the impact of LD 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. At the same time, a limitation of the study of Arbaugh (2014) is the exclusive focus on MBA modules, relying on self-reported data from students, which may limit generalisations of the findings to other disciplines. Similarly, our own study (Rienties et al., 2015) comparing 40 learning designs across the OU consisted of only a snapshot of modules per discipline and level using simple correlations, thereby again potentially lacking generalisability. We aim to address this gap by comparing the learning designs of 151 modules that were followed by over 110 k online students at different disciplines, levels, and programmes.

3. Method

3.1. OULDI learning design

The LD taxonomy used for this article was developed as a result of the Jisc-sponsored Open University Learning Design Initiative (OULDI) (Cross, Galley, Brasher, & Weller, 2012), and was developed over five years in consultation with eight Higher Education institutions. In contrast to instructional design, LD is process based (Conole, 2012); following a collaborative design approach in which practitioners make informed design decisions with a pedagogical focus through using representations in order to build a shared vision. This is especially relevant for institutions which deliver distance learning as it does not (yet) allow for ad-hoc changes as a result of timely observation of student behaviour as a teacher would do in a face-to-face setting. Collaborative design is also found to be more effective compared to teachers working as an individual (Hoogveld, Paas, & Jochems, 2003), also followed by the OU, based upon almost a decade of academic and institutional research (Cross et al., 2012).

For a detailed description of the seven learning descriptions and theoretical foundations, we refer to previous published work (Rienties et al., 2015; Toetenel & Rienties, 2016). *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 LA conceptualisations, the next five categories describe different options available to teachers to create an interactive, social learning environment (Buckingham Shum & Ferguson, 2012; Ferguson & Buckingham Shum, 2012; Hickey et al., 2014). By *finding and handling information*, for example on the internet or in a spreadsheet, learners take responsibility for their learning, which also is focussed on skills development in contrast to teacher-driven content. *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* endeavour to do the same, but in a safe setting, such as provided through 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.

3.2. Setting

This study took place at the OU, the largest higher education provider of online distance education in Europe. A process of “module mapping” or “coding learning activities” (i.e. analysing and providing visualizations of the learning activities and resources involved in a module) was introduced as part of a university-wide learning initiative (Rienties et al., 2016; Toetenel & Rienties, 2016) which aims to use LD data for quality enhancement. In addition to this institution-wide focus, academic colleagues in faculties often request for their modules to be mapped, in particular when reviewing or redesigning their courses. The mapping process is comprehensive, but labour intensive; typically taking between three and five days for a single module, depending on the module's number of credits, structure, and quantity of learning resources. A team of LD specialists reviewed all the available learning materials, classified the types of activity, and quantified 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 LD team held regular meetings to improve consistency across team members in the mapping process. Once the mapping process was complete, the LD team manager reviewed the module before the findings were sent to the faculty. Some faculties also mapped the modules themselves in order to compare both data sets. 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.

3.3. Instruments

3.3.1. Learning design mapping

The LD tool at the OU is a combination of graphical, text-based tools that are used in conjunction with LD workshop activities, which were mandated at particular times in the design process. In total 189 modules were mapped by the LD 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 VLE and 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). Modules at the OU vary widely in size, many modules have student populations over a thousand students where as some modules have much fewer students. 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 in the LD tools. Each activity within the module's weeks, topics, or blocks was categorized according to the LD taxonomy (see Table 1). These categorizations were captured in a visual representation in the form of an “activity planner” (or “blueprint”).

3.3.2. VLE data

In line with Tempelaar et al. (2015) and our previous work (Rienties et al., 2015), two different types of VLE data in Moodle were gathered per module in a static and dynamic manner: average time spend on VLE per week; and average time spent per session on VLE. Subsequent derivatives of these two types of data per week were recorded for week −3 until week 40 (data streams starts 2–3 weeks before the actual start of the module). Although more fine-grained LA 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 VLE. Such data was available for 141 modules.

3.3.3. 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 (Onwuegbuzie et al., 2007; Zerihun, Beishuizen, & Os, 2012), at the OU the Student Experience on a Module (SEaM) questionnaire was implemented. Following our analysis of key drivers amongst 65 K students' learning experience (Li et al., 2016), for this analysis we used the aggregate scores of five core items that drive learner

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.

satisfaction.

3.3.4. Academic retention

Our core 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 (Richardson, 2013) as the relationship between (lower) previous educational attainment and (lower) retention has been widely published.

3.3.5. Institutional analytics data

In line with previous studies (Arbaugh, 2014; Arbaugh & Duray, 2002; Marks, Sibley, & Arbaugh, 2005), we included several institutional analytics data that are known to influence the students' learning experience, such as the level of the course (Calvert, 2014), the specific discipline (Rienties et al., 2012), the year of implementation, size of the class or module (Arbaugh, 2014; Arbaugh & Duray, 2002; Marks et al., 2005).

3.4. Data analysis

All data were collected on an aggregate, module level. As a first step, we merged the LD data with the VLE and learner retention data based upon module ID and year of implementation. In total 151 module implementations could be linked with VLE learning behaviour 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 versus the total of 1016 module implementations that occurred at the university which were not mapped in the LD 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 LD team primarily focused on large scale undergraduate modules, this result was expected. All data were 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, in line with OU's ethics guidelines. Follow-up correlation and regression analyses were conducted using SPSS 21.

4. Results

4.1. Linking learning design activities

As a first step, we undertook Pearson correlation analyses to identify the relationships between the seven different LD activity types, as illustrated in Table 2. We found that assimilative activities were negatively related to all of the other six LD activities, indicating that focusing more on cognition and content reduced the focus on other activities. Similar to assimilative activities, assessment was negatively related to five of six LD activities, which may indicate that module teams implicitly or explicitly make a trade-off between these LD activities. Positive correlations were found between finding information and communication, and between productive and experiential. Total workload was positively related to communication and experiential and negatively to assessment, indicating that teachers dedicated relatively more time for social constructivist activities and fewer time for assessment. Although there were substantial differences in learning designs within each faculty, there were some common trends within each discipline. Faculty 1 modules had relatively fewer productive and experiential LD activities, and more assimilative activities. Faculty 2 had relatively more communication and productive activities, and fewer interactive and assessment activities. Faculty 3 modules had relatively more experiential activities, while fewer assimilative. Finally, significant negative correlations for communication and productive activities were found for modules designed by the Faculty 4, and a positive correlation was found for assessment.

4.2. Relating learning design with VLE behaviour

VLE data was not available for 10 out of the 151 modules, so we linked the learning designs of 141 modules followed by 111,256 learners with their VLE data. In total students spent 397,018,816.51 min online in the VLE. On average, students spent 94.34 min per week in the VLE ($SD = 55.30$, range 19.05–304.50), although in several modules students spent considerable more time during peak weeks, as illustrated in Fig. 1. This wide range in Fig. 1 highlights strong underlying differences in the way modules were designed. Similarly, in terms of the amount of time spent per visit students spent 17.46 min per login in the VLE ($SD = 6.34$, range 5.15–36.93), although in several modules students spent considerable more time per login during peak weeks, as illustrated in Fig. 2.

Some modules primarily relied on traditional methods of distance learning and course delivery via books and readers, with limited interactions in the VLE (Moore, 1989). Other modules provided most or all of their course materials, tasks and learning activities exclusively online and expected students to engage actively in the VLE during the week (Arbaugh, 2014). We caution our readers that VLE 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 (e.g., attending f2f sessions), informal (e.g., Facebook) or offline activities (e.g., reading printing materials).

VLE visits were positively related to communication activities and total (planned) workload, and negatively related to assessment activities. Average time spent in the VLE correlated positively with finding and handling information ($r = .318$, $p < .01$), communication activities ($r = .471$, $p < .01$), experiential ($r = .376$, $p < .01$) and total workload ($r = .456$, $p < .01$), whilst, a negative relation was found with assimilative activities ($r = -.300$, $p < .01$). As illustrated in Table 3, in Week −1 students in assimilative modules were spending less time in the VLE than students who had more experiential designs. From Week 1 onwards a consistent pattern between LD and average time spent in the VLE is found in Table 3. In other words, the LD decisions of teachers seemed to strongly influence how students were engaging with the VLE, in particular when more inquiry- or social constructivist learning activities were included in the learning design. More importantly, for researchers the fact that these patterns are measurable from the beginning of the module might provide useful indicators to control for differences in engagement across modules.

Table 4 illustrates four regression models of VLE engagement (per week and per visit), institutional analytics data, SEAM learner satisfaction, and the six LD activities, whereby we used post-graduate education, Faculty 4, and assimilative activities as respective reference groups. The levels range from 0 to 4, where level 0 refers to so-called access or foundation modules, level 1 to 3 refers to the three years an undergraduate spends at university, while level 4 refers to post-graduate education. In Average time per week spend in VLE Model 1, the regressions indicated that VLE engagement was significantly positively predicted by students who followed level 2 modules (in standardized betas). Institutional

Table 2
Correlation matrix of learning design and faculties.

	Mean	SD	1	2	3	4	5	6	7	8
1. Assimilative (in %)	42.17	16.77								
2. Finding information	4.14	5.45	−.402**							
3. Communication	4.50	5.37	−.437**	.517**						
4. Productive	14.93	11.08	−.407**	−.095	−.019					
5. Experiential	3.85	7.18	−.325**	.035	.247**	−.021				
6. Interactive	1.86	3.55	−.215**	.050	.030	−.022	.067			
7. Assessment	28.56	12.60	−.366**	−.068	−.201*	−.270**	−.258**	−.049		
8. Total workload (in hours)	229.41	113.08	−.064	.105	.296**	−.024	.407**	.032	−.306**	
9 Faculty 1 (in %)	15.47		.216**	.075	−.153	−.216**	−.228**	−.072	.086	−.276**
10 Faculty 2	18.69		−.041	.026	.286**	.171*	.075	−.168*	−.225**	.090
11 Faculty 3	18.53		−.172*	.154	−.052	.144	.205*	−.119	−.026	.193*
12 Faculty 4	26.05		.055	−.136	−.223**	−.166*	−.141	.009	.304**	.030

n = 151, *p < .05, **p < .01.

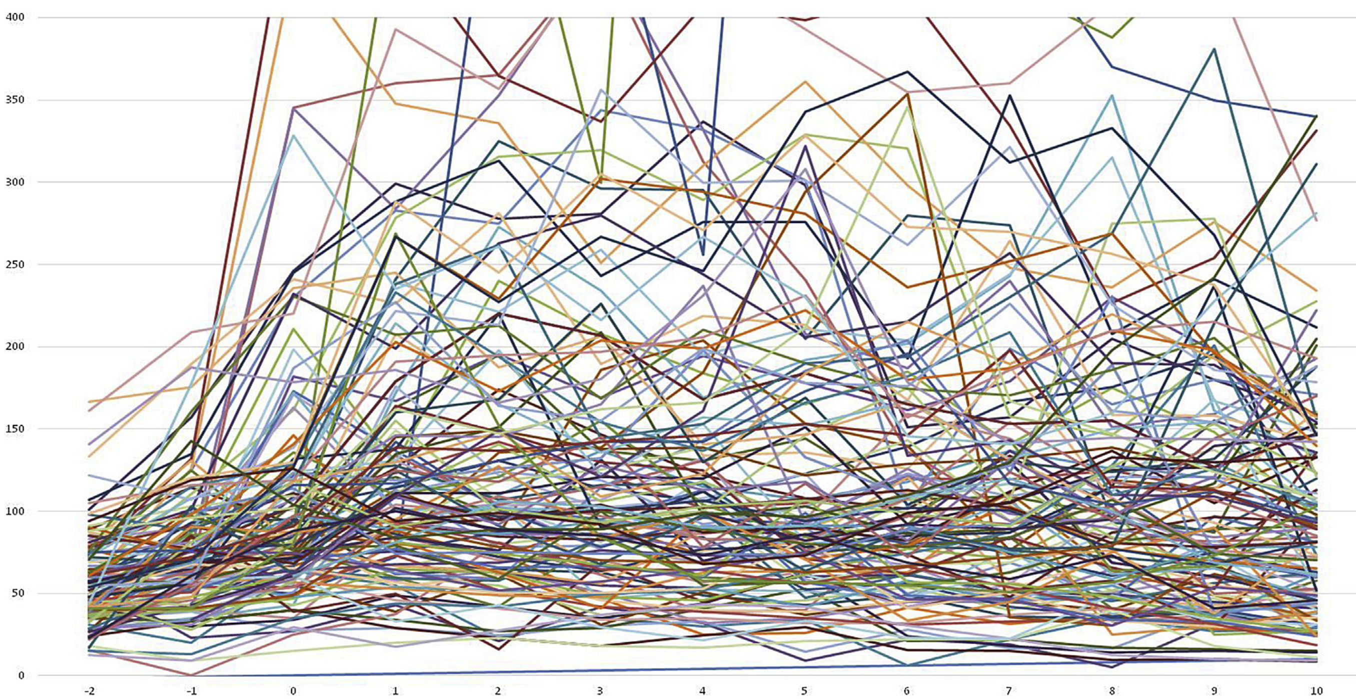

Fig. 1. VLE average time spent per week in minutes per module (n = 140).

variables such as disciplinary differences in Model 1 were significant predictors for Faculty 1 and 3, indicating that these disciplines had relatively lower VLE engagement relative to the reference group of Faculty 4. The size of the module, in terms of number of credits, significantly predicted VLE engagement, whereby larger modules had more online presence and more engagement. When adding the six LD activities in Model 2, communication and experiential learning activities were significantly positively predicting VLE engagement per week.

When using average VLE engagement per session in Model 3 and Model 4 (i.e., per log-in) rather than average VLE engagement per week, similar patterns emerged with the exception that in more recent implementations students seemed to spent more time per session online. The seven learning activities explained 29% and 13% of variance respectively, and when the institutional analytics and SEAM were included 20% and 13% of unique variance was explained respectively. In other words, the LD activities allow LA researchers to explain a significant part of variance in VLE behaviour of students across modules.

4.3. Relating learning design with learner satisfaction

As a next step, we linked the LD metrics with learner satisfaction. On average, 80.85% (SD = 11.06) of the 26,483 (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 ($r = -.224$, $p < .01$).

Table 5 illustrates four regression models of Average SEAM score, institutional analytics data, the six LD activities, and two VLE engagement proxies, with the same reference groups as before. In learner satisfaction Model 1, the regressions indicated that learner satisfaction was significantly predicted by students who followed the Level 0 access models, whom were significantly more positive than other modules. In Model 2, learner satisfaction was significantly negatively predicted by finding information, experiential and assessment learning activities, and positively predicted by

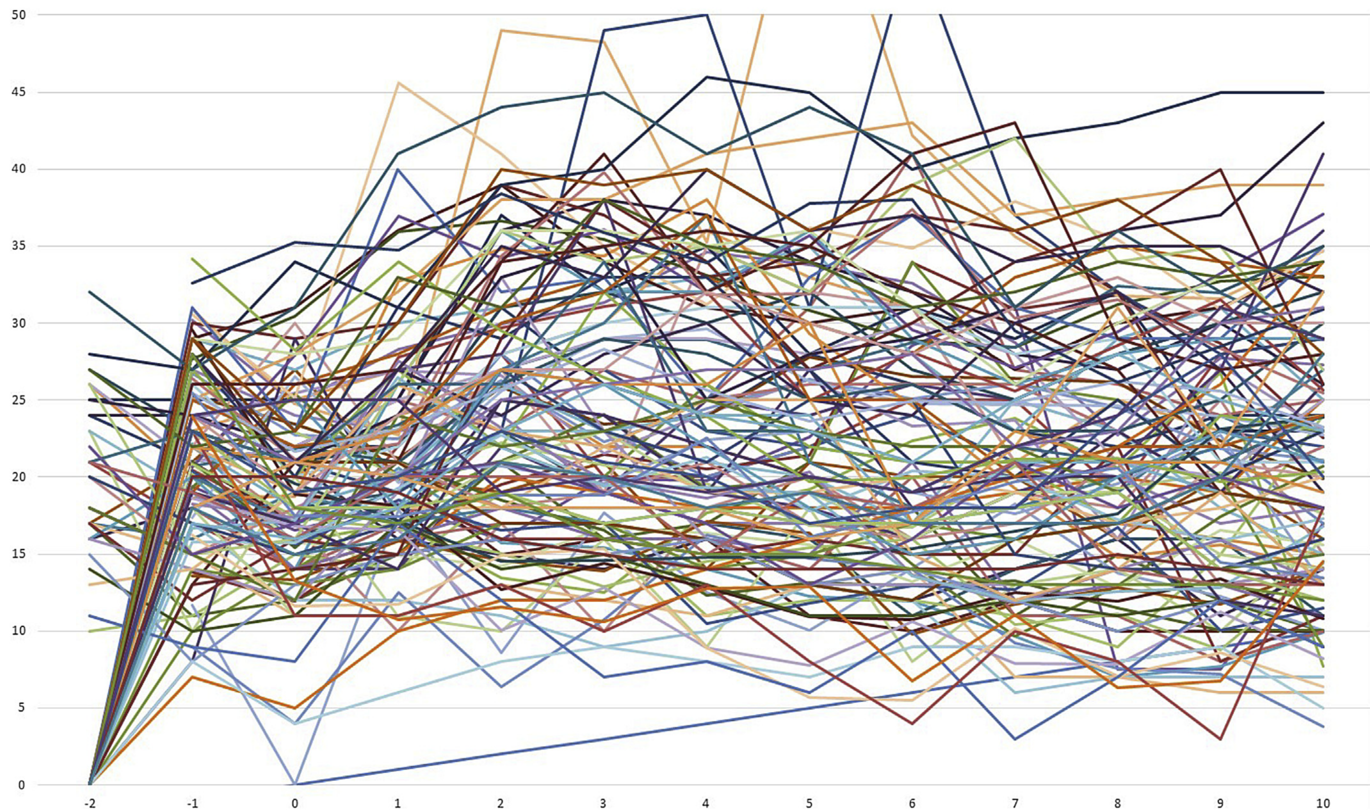

Fig. 2. VLE average time spent per visit in minutes per module (n = 140).

Table 3
Average time spent in VLE across the seven learning design activities (Week − 2 to Week 10).

Week	Assim	Find	Com.	Prod	Exp	Inter	Asses	Total
−2	−.03	.02	−.02	−.09	.20*	−.03	.01	.35**
−1	−.17*	.14	.14	−.01	.30**	−.02	−.05	.38**
0	−.21*	.14	.37**	−.07	.13	.08	.02	.48**
1	−.26**	.25**	.47**	−.02	.28**	.01	−.1	.48**
2	−.33**	.41**	.59**	−.02	.25**	.05	−.13	.42**
3	−.30**	.33**	.53**	−.02	.34**	.02	−.15	.51**
4	−.27**	.41**	.49**	−.01	.23**	−.02	−.15	.35**
5	−.31**	.46**	.52**	.05	.16	−.05	−.13	.28**
6	−.27**	.44**	.47**	−.04	.18*	−.09	−.08	.28**
7	−.30**	.41**	.49**	−.02	.22**	−.05	−.08	.33**
8	−.25**	.33**	.42**	−.06	.29**	−.02	−.10	.32**
9	−.28**	.34**	.44**	−.01	.32**	.01	−.14	.36**
10	−.34**	.35**	.53**	.06	.27**	.00	−.13	.35**

n = 141, *p < .05, **p < .01.

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 VLE engagement per week and per session to Model 3 and Model 4 respectively the primary predictors from Model 2 remained the same, and VLE engagement per session positively predicted learner satisfaction. The seven learning activities explained 13% of variance, and when the institutional analytics were included 10% of unique variance was explained. In other words, LD 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).

4.4. Relating learning design with learning performance

In terms of linking LD with learning performance, a significant negative correlation was found between assimilative activities and academic retention ($r = -.268$, $p < .01$), while a positive correlation was found in terms of communication ($r = .269$, $p < .01$). Subsequently, using regression modelling we predicted academic retention by three different models in Table 6. In Model 1, academic retention (i.e., % of students passed) 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. In Model 2, we added the LD activities and communication significantly and positively predicted academic retention. Finally, in Model 3 VLE engagement and learner satisfaction were not significantly predicting academic retention. The seven learning activities explained 11% of variance, and when the institutional analytics were included 5% of unique variance was explained. Separate analyses (not illustrated) with assessment rather than assimilative LD 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, communication seemed to be a key lever for retention in blended and online distance education at the OU.

5. Discussion

Pedagogy and learning design have traditionally been of key importance in online learning (Conole, 2012; Eysink et al., 2009),

Table 4
Regression model of VLE engagement (per week and per session) predicted by institutional, satisfaction and learning design analytics.

	Average time per week Model 1	Average time per week Model 2	Average time per session Model 3	Average time per session Model 4
Level0	−.279**	−.081	−.040	.135
Level1	−.341*	−.040	−.171	−.026
Level2	.221*	.256**	.245**	.257*
Level3	.128	.142	.157	.147
Year of implementation	.048	.085	.302**	.363**
Faculty 1	−.205*	−.176*	−.204*	−.181*
Faculty 2	−.022	−.226**	.032	−.095
Faculty 3	−.206*	−.287**	−.007	−.070
Faculty other	.216	.030	.147	−.020
Size of module	.210*	.238**	.283**	.330**
Finding information		.118		.119
Communication		.403**		.295*
Productive		.108		.060
Experiential		.346**		.343**
Interactive		−.059		.029
Assessment		.054		.121
R-sq adj	19%	39%	17%	30%

n = 140, *p < .05, **p < .01.

Table 5
Regression model of learner satisfaction predicted by institutional analysis, learning design analytics, VLE engagement and satisfaction.

	Model 1	Model 2	Model 3	Model 4
Level0	.284**	.304**	.351**	.330**
Level1	.259	.243	.265	.245
Level2	−.211	−.197	−.212	−.237*
Level3	−.035	−.029	−.018	.008
Year of implementation	.028	−.071	−.059	−.097
Faculty 1	.149	.188	.213*	.252**
Faculty 2	−.039	.029	.045	.061
Faculty 3	.090	.188	.236*	.239**
Faculty other	.046	.077	.051	.065
Size of module	.016	−.049	−.071	−.119
Finding information		−.270**	−.294**	−.306**
Communication		.005	.050	.049
Productive		−.243**	−.274**	−.284**
Experiential		−.111	−.105	−.110
Interactive		.173*	.221*	.228**
Assessment		−.208*	−.221*	−.239**
VLE engagement per week			.117	
VLE engagement per visit				.192*
R-sq adj	20%	30%	31%	33%

n = 150 (Model 1–2), 140 (Model 3–4), *p < .05, **p < .01.

Table 6
Regression model of learning performance predicted by institutional, learning design analytics, VLE engagement and satisfaction.

	Model 1	Model 2	Model 3
Level0	−.142	−.023	.005
Level1	−.227	−.006	.094
Level2	−.134	−.009	.000
Level3	.059	.194	.238
Year of implementation	−.191**	−.196*	−.214*
Faculty 1	.355**	.362**	.388**
Faculty 2	−.033	−.141	−.155
Faculty 3	.095	.091	.056
Faculty other	.129	.045	.055
Size of module	−.298**	−.275**	−.287**
Finding information		−.166	−.174
Communication		.385**	.507**
Productive		.144	.146
Experiential		−.078	.022
Interactive		−.087	−.066
Assessment		.066	.051
VLE Engagement per week			−.229
VLE Engagement per session			.075
Learner satisfaction (SEAM)			−.091
R-sq adj	30%	35%	35%

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

but as a result of the lack of empirical data, research has not extensively linked LD to learning behaviour and learner performance (Kirschner, Sweller, & Clark, 2006; Rienties et al., 2012). In the UK the OU has been leading developments in data gathering through a comprehensive LD system, which allows for designs to be mapped by academics. Furthermore, this data source has been linked with actual learning behaviour and learner outcomes (Rienties et al., 2016; Toetenel & Rienties, 2016) and although these remain proxies, they are important indicators that help compare differences in student behaviour across modules. Building on our first study (Rienties et al., 2015), this study has provided strong empirical evidence that LD had a significant influence on learning activities, learner satisfaction and academic retention amongst 151 modules followed by 113.725 students.

Our first and perhaps most important finding is that learning design activities strongly influenced academic retention. A major step forward from our initial study with 40 modules (Rienties et al.,, 2015) 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. The primary predictor of academic retention was the relative amount of communication activities. This may be an important finding as in particular in online learning there tends to be a focus on designing for cognition rather than social learning activities (Arbaugh, 2014; Koedinger et al., 2013; Rienties et al., 2012), while recently several researchers have encouraged teachers and researchers to focus on the social elements of learning (Arbaugh, 2014; Ferguson & Buckingham Shum, 2012).

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 (Arbaugh, 2014; Onwuegbuzie et al., 2007; Zerihun et al., 2012) 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 6. More importantly, the (student-centred) LD activities that had a negative effect on learner experience had a neutral to even positive effect on academic retention.

Two possible explanations may be provided for the widely different effects of LD 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 (Kirschner et al., 2006; Koedinger et al., 2013) 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 seem to 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, but ongoing institutional work which analysed non-respondents has shown that their demographics and progression were not significantly different to those who did respond to the survey (Li et al., 2016). Even so, in certain modules actual dropout was well above 50%, which could indicate that students were "voting with their feet" when the LD and/or delivery did not meet their learning needs, although we acknowledge that many other reasons should be considered. An exclusive focus on learner satisfaction might distract institutions from understanding the impact of LD on 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.

6. Conclusions and future work

A major innovation of this study is that we were able to link the learning designs of 151 modules with VLE engagement, satisfaction and retention, whereby we were able to control for common institutional analytics factors and disciplinary differences. While a vast body of literature in the last ten years has conceptually indicated that learning design decisions by teachers may influence learners' behaviour and outcomes, to the best of our knowledge we are the first to empirically test the impact of learning design on behaviour and outcomes. In the near future, we hope to extend this sample further when more data becomes available in order to better understand the complex (inter)relations of LD on learning processes and outcomes as we will be able to combine this with further data sets such as student and teacher 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 help predict the impact of a particular LD on the satisfaction and outcomes of a particular subgroup of learners.

In terms of practical implications, researchers, teachers and policy makers need to be aware of how LD choices made by teachers influence subsequent learning processes and learning performance over time. Following Arbaugh (2005), 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 LD activities impact the learning journeys of our students.

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Dr Bart Rienties is Reader in Learning Analytics at the Open University, United Kingdom. His research interests include learning analytics, collaborative learning environments and the role of social interaction in learning.

Lisette Toetenel is a Learning Design project officer at the Open University, United Kingdom. Her research interests range from Learning Design and Learning Analytics to social media in education.