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

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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.

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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