Unravelling the dynamics of learning design within and between disciplines in higher education using learning analytics

Quan Nguyen
Open University the UK
Institute of Educational Technology
+44 7732599001
Quan.Nguyen@open.ac.uk

ADVISORS:
Bart Rienties, Denise Whitelock, Zdenek Zdrahal.
The Open University

ABSTRACT

Designing effective learning experience in virtual learning environment (VLE) can be supported by learning analytics (LA) through explicit feedback on how learning design (LD) influences students' engagement, satisfaction and performance. Marrying LA with LD not only puts existing pedagogical theories in instructional design to the test with actual learning data, but also provides the context of learning which helps educators translate established LA findings to direct interventions. My dissertation aims at unpacking the complexity of LD and its impact on students' engagement, satisfaction and performance on VLE using LA. The context of this study is 400+ online and blended learning modules at the Open University (OU) UK. This research combines multiple sources of data from the OU Learning Design Initiative (OULDI), system log data, self-reported surveys, and performance data. Given the scope of this study, a wide range of visualization techniques, social network analysis, multi-level modelling, and machine learning will be used.

Keywords
Learning analytics, learning design, engagement, satisfaction, retention, performance

1. INTRODUCTION

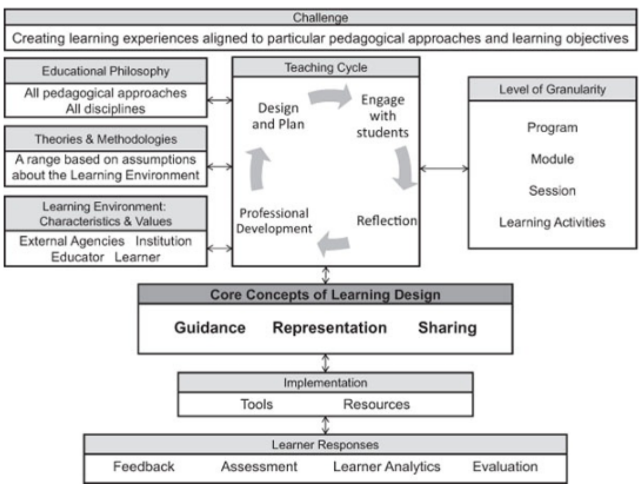
In the last decade, there is a growing body of literature [1-3] that seeks to develop a descriptive framework to capture teaching, and learning activities so that teaching ideas can be shared and reused from one educator to another, so called Learning Design (LD) [4]. A common metaphor of a learning design was a music notation which contains enough information to convey musical ideas from one to another over time and space [4]. Extensive research has been conducted focusing on technological implementations of LD such as the Educational Modelling Language (EML) [5], the SoURCE project [6], the Australian Universities Teaching Council (AUTC) LD project [7], and the Learning Activity Management System (LAMS) [8]. While the early work in LD have focused on transferring the design for learning from implicit to explicit, the relationship between LD and the actual learners' response has been not fully understood. Recently, the advancement in technology has allowed us to capture the digital footprints of learning activities from Virtual Learning Environment (VLE). This rich and fine-grained data about the actual learners' behaviors offer educators potentially valuable insights on how students react to different LDs.

Learning analytics (LA) has the potential to empower teachers and students by identifying patterns and trends from a wide variety of learners' data. Within the LAK community, substantial progress has been made both in conceptual development [9, 10] as well as how to design appropriate predictive LA to support students [11, 12]. Nonetheless, in line with [11, 13], findings from LA research have been rather limited to delivering actionable feedback, while ignoring the context in which the learning data is situated. Thus, within the LAK community there is an increasing interest to align LA with LD, as the former facilitates the transfer of tacit educational practice to an explicit rendition, while the latter provides educators with pedagogical context for interpreting and translating LA findings to direct interventions [14-18]. While there are abundant discussions on the value and impact of integrating LD into LA to improve teacher inquiry [17, 18], only a few studies have explicitly examined how teachers actually design their courses and whether LD influences satisfaction, VLE behavior, and retention [13, 19-21]. However, these studies have only explored LD from a static perspective, without accounting for the differences within and between modules and the possible interaction between different learning activities over time. Thus, my dissertation will empirically examine how teachers design their course within and between modules over time on a large scale study of 400+ modules at the Open University using multiple date sources.

2. ALIGNING LA WITH LD

In the last five years, LA has attracted a lot of attention from practitioners, management, and researchers in education by shedding light on a massive amount of (potentially) valuable data in education, as well as providing means to explicitly test existing pedagogical theories. Scholars in the field of LA have exploited various sources of data, such as activity logs of students [22], learning dispositions [23, 24], or discussion forum [25, 26]. By taking advantage of advanced analytical techniques such as predictive modeling [24], discourse analytics [27], machine learning [28], LA has succeeded in uncovering meaningful patterns and trends occurred during the learning process. While these studies provided important markers on the potential of LA in education, critics have indicated a gap between pedagogy and LA [29-31]. Interesting patterns can be identified from student activities, such as number of clicks, discussion posts, or essays. However, these patterns alone are not sufficient to offer feedback that teachers can put into actions [12, 32]. Without a pedagogically sound approach to data, LA researchers struggle with deciding which variables to attend to, how to generalize the results to other contexts, and how to translate their findings to actions [31]. Hence, LD can equip researchers with a story behind their numbers, and convert trends of data into meaningful understandings and opportunities to make sensitive interventions.

The core concepts of LD are best summarized in the Learning Design Conceptual Map (LD-CM) (Figure 1). It starts with the main objective of "creating learning experiences aligned to particular pedagogical approaches and learning objectives". How educators make decision about designing for learning is determined by Characteristics & Values of the learning environment, the educational philosophy, and theories and methodologies. In a interview based study of 30 participants, Bennett, Agostinho and Lockyer [33] identified three main factors that influenced how teachers engage in the designing process: student-related factors (cohort profile, learning objectives, feedback from past sessions), teachers-related factors (beliefs about teaching, prior experiences), and context-related factors (colleagues, institutional policies and culture, resources such as workload, time, and infrastructure).



. **Figure 1: A Learning Design Conceptual Map. Retrieved from** Dalziel, Conole, Wills, Walker, Bennett, Dobozy, Cameron, Badilescu-Buga and Bower [4]

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

2.1 Connecting LD and LA

Since the beginning of the 21st century, the term learning design has emerged as a "methodology for enabling teachers/designers to make more informed decisions in how they go about designing learning activities and interventions, which is pedagogically informed and makes effective use of appropriate resources and technologies" [1]. Several approaches for designing learning have been proposed, yet, one common stage in almost every approach was the evaluation of the LD [16, 34]. Persico and Pozzi [16] argued that the learning process should not only depend on experience, or best practice of colleagues but also pre-existing aggregated data on students' engagement, progression, and achievement. In a similar manner, Mor, Ferguson and Wasson [17] suggested that LA could facilitate teacher inquiry by transforming knowledge from tacit to explicit, and perceive students and teachers as participants of a reflective practice. For instance, in a study of 148 learning designs by Toetenel and Rienties [35], the introduction of a systematic LD initiative consisting of visualization of initial LDs and workshops helped educators to focus on the development of a range of skills and more balanced LDs. Feeding information on how students are engaged in a certain LD during or post-implementation can provide a more holistic perspective of the impact of learning activities [14].

Several conceptual frameworks aiming at connecting LA with LD have been proposed. Persico and Pozzi [16] discussed three dimensions of LD that can be informed by LA: representations, tools, and approaches. Lockyer, Heathcote and Dawson [14] introduced two categories of analytics applications: checkpoint analytics to determine whether students have met the prerequisites for learning by assessing relevant learning resources, and process analytics to capture how learners are carrying out their tasks. In the recent LAK conference 2016, Bakharia, Corrin, de Barba, Kennedy, Gašević, Mulder, Williams, Dawson and Lockyer [18] proposed four types of analytics (temporal, tool specific, cohort, and comparative), and contingency and intervention support tools with the teacher playing a central role.

While there were numerous discussions in aligning LA with LD, the amount of empirical studies on the subject has been rather limited. For example, Gašević, Dawson, Rogers and Gasevic [12] examined the extent to which instructional conditions influence the prediction of academic success in nine undergraduate courses offered in a blended learning model. The results suggested that it is imperative for LA to taking into account instructional conditions across disciplines and course to avoid over-estimation or underestimation of the effect of LMS behavior on academic success. From my preliminary literature review, most of the empirical studies attempting to connect LA and LD are derived from students activities [14], or differences in discipline [12], rather than the actual learning design [36].

Previous research has highlighted explicitly the role of LD in explaining LMS behavior, student satisfaction, retention, and differences in prediction of academic success [12, 13, 19-21]. For example, in a study linking 40 LDs with VLE behavior and retention, Rienties, Toetenel and Bryan [20] found that strongly assimilative designs (i.e., lots of passive reading and watching of materials) were negatively correlated with retention [20]. In a large-scale follow-up study using a larger sample of 151 modules and multiple regression analyses of 111,256 students at the Open University, UK, Rienties and Toetenel [19] revealed relations between LD activities and VLE behavior, student satisfaction, and retention. The findings showed that taking the context of LD into account could increase the predictive power by 10-20%. Furthermore, from a practitioner's perspective, the combination of a collaborative, networked approach at the initial design stage, augmented with visualizations, changed the way educators design their courses [35]. While these three studies at the Open University UK (OU) highlighted the potential affordances of marrying LD with LA on a large scale, two obvious limitations of these studies were the aggregation of learning design activities in predicting behavior and performance (i.e., rather than their interaction), as well as the static rather than longitudinal perspective of LD. In these studies [13, 20], aggregate learning design data across the 40 weeks of each module were used, while in many instances teachers use different combinations of learning activities throughout the module [36]. While fine-grained longitudinal data of LD per week were not available during the initial implementation phase of LD at the OU, in the last year fine-grained weekly LD data has been added, which would allow scholars to potentially identify the optimum mix of LD activities per discipline, level, and type of students per week and over time.

Table 1: Learning design taxonomy

	Type of activity	Example
Assimilative	Attending to information	Read, Watch, Listen, Think about, Access.
Finding and handling information	Searching for and processing information	List, Analyse, Collate, Plot, Find, Discover, Access, Use, Gather.
Communication	Discussing module related content with at least one other person (student or tutor)	Communicate, Debate, Discuss, Argue, Share, Report, Collaborate, Present, Describe.
Productive	Actively constructing an artefact	Create, Build, Make, Design, Construct, Contribute, Complete,.
Experiential	Applying learning in a real-world setting	Practice, Apply, Mimic, Experience, Explore, Investigate,.
Interactive /adaptive	Applying learning in a simulated setting	Explore, Experiment, Trial, Improve, Model, Simulate.
Assessment	All forms of assessment (summarive, formative and self assessment)	Write, Present, Report, Demonstrate, Critique.

In this study, I will use the LD taxonomy developed by Conole [1] (Table 1). Both conceptual and empirical research has found that the Open University Learning Design Initiative (OULDI) can accurately and reliably determine how teachers design courses, and how students are subsequently using these LDs [19, 21].

2.2 Research Questions & Proposed timeline

Year	Research questions
1	How are learning designs configured across modules over time in VLE?
	How do different learning activities interact with each other across modules in VLE?
2	How do learning designs affect students' engagement over time in VLE?
	How do learning designs affect satisfaction in VLE?
	How do learning designs affect performance over time in VLE?
3	How do learning designs affect students' engagement, satisfaction, and performance in blended and face-to-face learning environment?

3. METHODOLOGY

3.1 Data sources

In the first stage of my study, I will use data generated from the OULDI. For a detailed description of how each learning design was mapped, I refer readers to Rienties and Toetenel [19]. In parallel, data retrieved from students' log activities, self-reported surveys on satisfactions, and academic performance will also be incorporated. An expected number of 400+ modules scattering across a wide range of disciplines, levels (undergrad, postgrad), number of credits, blended, or distant learning could potentially be used for the analysis.

In the second stage, a sample of at least 1000+ students taking a blended course in statistics at Maastricht University can be used to verify my findings in a more traditional teaching setting.

3.2 Instruments

3.2.1 Measurement of learning design

Seven LD variables were measured in terms of workload, which is the number of hours that students are expected to study. Time spent on learning activities was restricted based on the size of the module, such as 30 credits equated to 300 hours of learning, and 60 credits equated to 600 hours of learning.

3.2.2 Measurement of students' engagement in VLE

In line with Tempelaar, Rienties and Giesbers [24] and Rienties and Toetenel [19], two different types of VLE data were gathered per module in a static and dynamic manner: average time spent (in minutes) on VLE per week, and average time spent per visit (in minutes) on VLE. It should be noted that these crude measurements of VLE only represented the average time a student spent on VLE platform, not the actual studying time, as this can be affected by unobservable factors, such as when students study offline, or using non-OU systems such as Facebook (which the OU does not monitor). Further research will be conducted to provide accurate and meaningful measurements on students' engagement in VLE.

3.2.3 Measurements of students' satisfaction

In line with previous research on student learning experience [37, 38], at the OU, the Student Experience on a Module (SEaM) questionnaire is implemented which includes 40 questions in 5 categories: Guidance & Support, Content & Expertise, Communication & Collaboration, Reflections & Demonstration, and Key Performance Indicators (KPIs).

3.2.4 Measurements of students' performance

Tutor marked assignments and electronic marked assignments will provide proxies for academic performance of students.

3.3 Data analysis

A combination of visualization, social network analysis, and multi-level modelling are expected to be used in this large scale study. Artificial neuron network techniques could also be implemented when fine-grained data on learning activities become available.

4. INITIAL FINDINGS

In my recent LAK17 submission, a longitudinal study on 38 modules with a total of 43,099 registered students over 30 weeks at the Open University UK was conducted to investigate how learning design was configured over time and its impact on student activities using social network analysis, and panel data analysis.

Firstly, the dynamic visualization on the LD of each module over time revealed that the use of LD varied considerably across modules and disciplines (Figure 1). A balanced approach of LD can be seen in module 2 in the Business and Law faculty, in which it consists of six out of seven LDs with equally distributed workloads for each activity and each week. When there was an assessment, the workload on other activities were reduced to avoid the overwhelming workload on students. This is a very important remark for teachers and course designers since learners (especially those are working full-time or part-time) can be sensitive to peaks and troughs in workload, which in turn may damage their learning experience. Such example could be observed in module 1 in Art and Social Science discipline, in which there was a huge surge in the workload in week 10, which was more than 20 hours for all learning activities, compared with the average of 9 hours per week. Another example of a potentially unbalanced design was module 3 in the Faculty of Education and Language studies, which only used three types of LD throughout the course (i.e., assimilative, assessment, and productive).

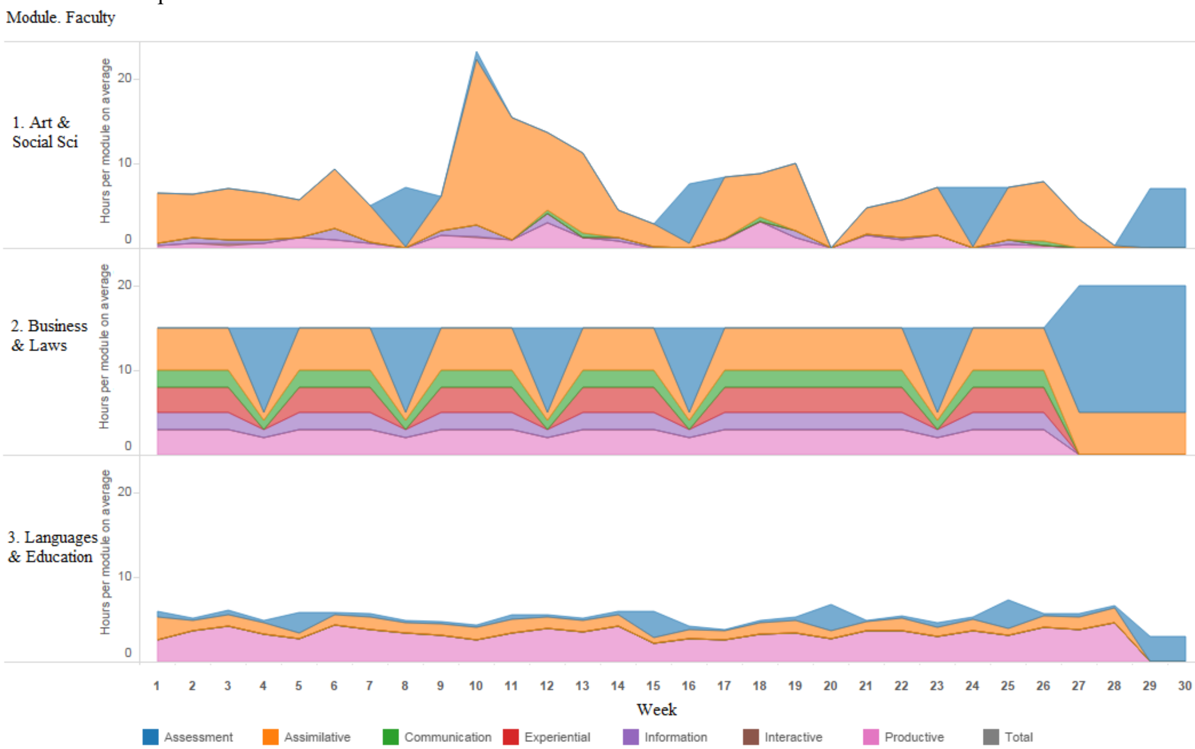
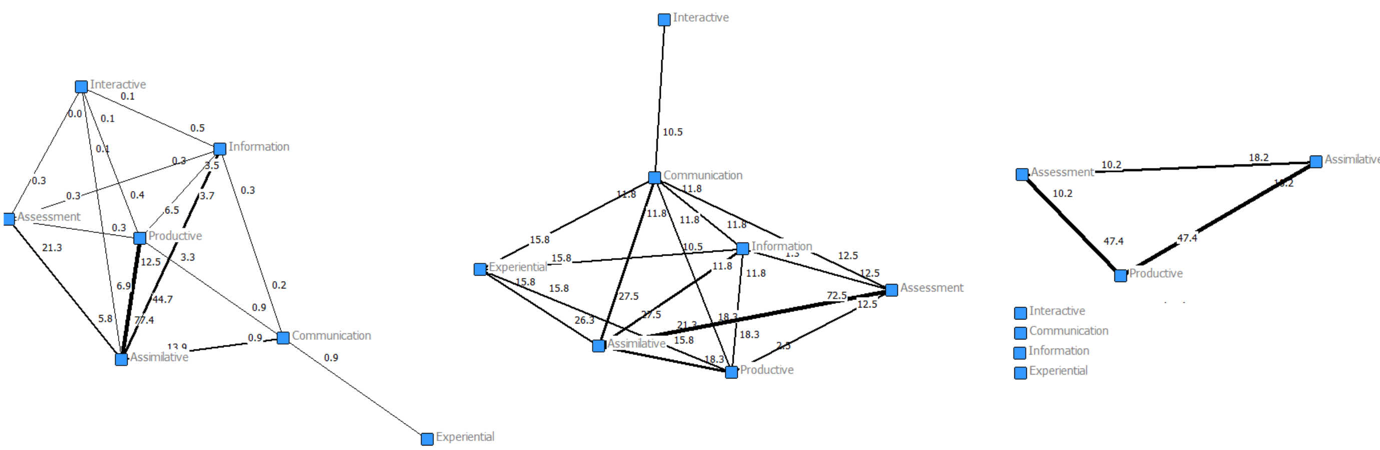


Figure 1: Feature modules



1. Art & Social Science

2. Business & Laws

3. Languages and Education

Figure 2: Social network analysis of three exemplar modules

Secondly, using SNA, it was able to observe how different learning designs were connected to each other (Figure 2). The results suggested that if we concentrate on a single component of learning design in isolation, we might omit the complexity and critical features of the instructional dynamic. By adopting the view of system of practice [39], the empirical evidence strengthened the view of Hora and Ferrare [36] which indicated that teachers perceive certain learning designs as being meant for each other (i.e. assimilative & productive, communication & experiential) and these perceptions varies across disciplines. Interestingly, even though certain disciplines exhibited favorable practice towards a particular learning activity, each module utilized it with other learning activities in different ways. For example, it is apparent that assimilative activities were the most common learning design in all three exemplar modules. However, the repertoire of practice in module 1 (assimilative, information, and productive) was different from module 2's (assimilative, information, communication, experiential, and productive) and module 3's (assimilative, assessment, and productive). Overall, LD is best viewed in relation to one another in multiple dimensions throughout time.

The final takeaway is by taking into account the context of learning across 38 modules, learning designs could explain up to 60% of the variance of the time spent on VLE platform (Table 1-2, Appendix). Even though significant effects of certain learning design on VLE activities were identified in the analysis, we advise readers to interpret them with cautions. As discussed above, learning design should be perceived in relation with one another rather than in isolation. For example, the results showed that students spent less time on VLE when they engaged in productive activities. However, this did not imply that by simply cutting down productive activities, students will be more likely to engage. It is because each module employed productive activities in relation with different learning activities in different ways at different points in time.

5. IMPLICATIONS

From a practitioner's perspective, this dissertation not only helps educators reflect on their practice as well as compare and contrast with others, but also provides feedback on whether their learning design is steering the students towards the desired directions. Which repertoire of practice would encourage students' engagement on VLE? Which learning activities would improve the learning experience? Which learning design would facilitate their understanding of the subject? These are the questions that this research will be able to answer.

From a researcher's perspective, this study provides a platform consisting of a large number of modules using multiple datasets to put existing educational theories in the test on a large sample.

6. FUTURE WORK

In the first year of my Ph.D., I will focus on building up a theoretical framework either through an extensive literature review or multiple pilot studies. At the same time, I will ensure and develop accurate and meaningful measurements of LD, engagement, satisfaction, and performance.

In my second year, I will explicitly study the effect of LD on multiple dimensions of students as mentioned above. For instance, social network metrics of LD can be incorporated in the prediction models. When more fine-grained data (i.e. how much time students are expected to spend on writing essays, watching video, listening to audio, etc.) become available, I can unfold the complexity of LD in a more specific manner. Multi-level analysis can be conducted on a large scale study to account for the heterogeneity across faculties, levels of study, modules, and configurations of learning design

In my final year, I expect to verify my findings in a more traditional learning environment such as blended learning or face-to-face learning.

7. REFERENCES

[1] Conole, G. *Designing for learning in an open world*. Springer Science & Business Media, 2012.

[2] Dalziel, J. *Learning design: Conceptualizing a framework for teaching and learning online*. Routledge, New York, NY, USA, 2015.

[3] Lockyer, L., Bennett, S., Agostinho, S., Harper, B., Lockyer, L., Bennett, S., Agostinho, S. and Harper, B. *Handbook of Research on Learning Design and Learning Objects: Issues, Applications and Technologies*. IGI Global, New York, NY, USA, 2008.

[4] Dalziel, J., Conole, G., Wills, S., Walker, S., Bennett, S., Dobozy, E., Cameron, L., Badilescu-Buga, E. and Bower, M. The Larnaca declaration on learning design. *Journal of Interactive Media in Education*, 2016, 1 2016), 1-24.

[5] Koper, R. and Manderveld, J. Educational modelling language: modelling reusable, interoperable, rich and personalised units of learning. *British Journal of Educational Technology*, 35, 5 2004), 537-551.

[6] Laurillard, D. and McAndrew, P. *Virtual Teaching Tools: Bringing academics closer to the design of e-learning*. City, 2001.

[7] AUTCLearningDesign *Predict–Observe–Explain: Designer's Voice–Context*. City, 2002.

[8] Dalziel, J. *Implementing learning design: The learning activity management system (LAMS)*. University of Adelaide, City, 2003.

[9] Ferguson, R. Learning analytics: drivers, developments and challenges. *International Journal of Technology Enhanced Learning*, 4, 5-6 2012), 304-317.

[10] Clow, D. An overview of learning analytics. *Teaching in Higher Education*, 18, 6 2013), 683-695.

[11] Joksimović, S., Gašević, D., Loughin, T. M., Kovanović, V. and Hatala, M. Learning at distance: Effects of interaction traces on academic achievement. *Computers & Education*, 872015), 204-217.

[12] Gašević, D., Dawson, S., Rogers, T. and Gasevic, D. Learning analytics should not promote one size fits all: The effects of instructional conditions in predicting academic success. *The Internet and Higher Education*, 282016), 68-84.

[13] Rienties, B. and Toetenel, L. *The impact of 151 learning designs on student satisfaction and performance: social learning (analytics) matters*. ACM, City, 2016.

[14] Lockyer, L., Heathcote, E. and Dawson, S. Informing pedagogical action: Aligning learning analytics with learning design. *American Behavioral Scientist*, 57, 10 2013), 1439 - 1459.

[15] Lockyer, L. and Dawson, S. *Learning designs and learning analytics*. ACM, City, 2011.

[16] Persico, D. and Pozzi, F. Informing learning design with learning analytics to improve teacher inquiry. *British Journal of Educational Technology*, 46, 2 2015), 230-248.

[17] Mor, Y., Ferguson, R. and Wasson, B. Editorial: Learning design, teacher inquiry into student learning and learning analytics: A call for action. *British Journal of Educational Technology*, 46, 2 2015), 221-229.

[18] Bakharia, A., Corrin, L., de Barba, P., Kennedy, G., Gašević, D., Mulder, R., Williams, D., Dawson, S. and Lockyer, L. *A conceptual framework linking learning design with learning analytics*. ACM, City, 2016.

[19] Rienties, B. and Toetenel, L. The impact of learning design on student behaviour, satisfaction and performance: A cross-institutional comparison across 151 modules. *Computers in Human Behavior*, 602016), 333-341.

[20] Rienties, B., Toetenel, L. and Bryan, A. *Scaling up learning design: impact of learning design activities on lms behavior and performance*. ACM, City, 2015.

[21] Toetenel, L. and Rienties, B. Analysing 157 learning designs using learning analytic approaches as a means to evaluate the impact of pedagogical decision making. *British Journal of Educational Technology*2016).

[22] Macfadyen, L. P. and Dawson, S. Mining LMS data to develop an "early warning system" for educators: A proof of concept. *Computers & education*, 54, 2 2010), 588-599.

[23] Nguyen, Q., Tempelaar, D. T., Rienties, B. and Giesbers, B. What learning analytics based prediction models tell us about feedback preferences of students. *Quarterly Review of Distance Education*, 17, 3 2016), 13-33.

[24] Tempelaar, D., Rienties, B. and Giesbers, B. In search for the most informative data for feedback generation: Learning Analytics in a data-rich context. *Computers in Human Behavior*, 472015), 157-167.

[25] Bakharia, A. and Dawson, S. *SNAPP: a bird's-eye view of temporal participant interaction*. ACM, City, 2011.

[26] Wise, A. F., Cui, Y., Jin, W. and Vytasek, J. Mining for gold: Identifying content-related MOOC discussion threads across domains

through linguistic modeling. *The Internet and Higher Education*, 322017), 11-28.
[27] Whitelock, D., Twiner, A., Richardson, J. T., Field, D. and Pulman, S. *OpenEssayist: a supply and demand learning analytics tool for drafting academic essays*. ACM, City, 2015.
[28] Kuzilek, J., Hlosta, M., Herrmannova, D., Zdrahal, Z. and Wolff, A. OU Analyse: analysing at-risk students at The Open University. *Learning Analytics Review*2015), 1-16.
[29] Gašević, D., Dawson, S. and Siemens, G. Let's not forget: Learning analytics are about learning. *TechTrends*, 59, 1 2015), 64-71.
[30] Wise, A. F. and Shaffer, D. W. Why theory matters more than ever in the age of big data. *Journal of Learning Analytics*, 2, 2 2015), 5-13.
[31] Kirschner, P. A. *Keynote: Learning Analytics: Utopia or Dystopia*. City, 2016.
[32] Rienties, B., Boroowa, A., Cross, S., Kubiak, C., Mayles, K. and Murphy, S. Analytics4Action Evaluation Framework: A Review of Evidence-Based Learning Analytics Interventions at the Open University UK. *Journal of Interactive Media in Education*, 2016, 1 2016).
[33] Bennett, S., Agostinho, S. and Lockyer, L. Technology tools to support learning design: Implications derived from an investigation of university teachers' design practices. *Computers & Education*, 81(2// 2015), 211-220.
[34] MacLean, P. and Scott, B. Competencies for learning design: A review of the literature and a proposed framework. *British Journal of Educational Technology*, 42, 4 2011), 557-572.
[35] Toetenel, L. and Rienties, B. Learning Design–creative design to visualise learning activities. *Open Learning: The Journal of Open, Distance and e-learning*, 31, 3 2016), 233-244.
[36] Hora, M. T. and Ferrare, J. J. Instructional systems of practice: A multidimensional analysis of math and science undergraduate course planning and classroom teaching. *Journal of the Learning Sciences*, 22, 2 2013), 212-257.
[37] Zerihun, Z., Beishuizen, J. and Van Os, W. Student learning experience as indicator of teaching quality. *Educational Assessment, Evaluation and Accountability*, 24, 2 2012), 99-111.
[38] Onwuegbuzie, A. J., Witcher, A. E., Collins, K. M., Filer, J. D., Wiedmaier, C. D. and Moore, C. W. Students' perceptions of characteristics of effective college teachers: A validity study of a teaching evaluation form using a mixed-methods analysis. *American Educational Research Journal*, 44, 1 2007), 113-160.
[39] Halverson, R. R. Systems of practice: How leaders use artifacts to create professional community in schools. *education policy analysis archives*, 112003), 37.

8. APPENDIX

Table 1: Panel data analysis of the effect of learning design on the average time spent on VLE per visit

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

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

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

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

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