Analysing 157 Learning Designs using Learning Analytic approaches as a means to evaluate the impact of pedagogical decision-making

Journal Article

Analysing 157 Learning Designs using Learning Analytic approaches as a means to evaluate the impact of pedagogical decision-making.

Lisette Toetenel and Bart Rienties

Lisette Toetenel is a Learning Design project officer at the Open University (OU), United Kingdom. Her research interests range from Learning Design and Learning Analytics to social media in education. 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. Address for correspondence: Lisette Toetenel, Jennie Lee Building, Walton Hall Campus, Milton Keynes, MK7 6AA. Email: Lisette.Toetenel@open.ac.uk.

Practitioner Notes

What is already known about this topic

· Learning Design can be applied at various granularity in educational design, at activity, course or qualification level.

· Learning Design intends to visualise traditionally 'tacit' decisions made by educators in order to share good practice.

· Learning and teaching activities considered as 'good practice' are often not empirically evaluated.

· Combining Learning Design with Learning Analytics helps to provide a context for the empirical data and enables researchers to empirically investigate Learning Design decisions.

What this paper adds

· Empirically investigates pedagogical decisions made in 157 courses, undertaken by over 60000 students, responding to previous calls for research using large data sets.

· Visualises most common activities used in the data set

· Links student outcomes to Learning Design decisions made; links design to performance.

Implications for practice and/or policy

·By 'scaling up' empirical research in Learning Design, relationships between Learning Design and student outcomes help to improve future course design.

· Senior managers in HE might find these visualisations helpful in deciding what their curriculum should look like, e.g. providing practical guidance for their staff.

Insert Abstract about here

Introduction

Educators continuously need to adapt to a shifting educational context, in order to advance educational objectives (Mor, Craft, & Hernández-Leo, 2013). Both the context and educational objectives are continuously changing, as the objectives set by society follow technological advancements. Whereas educators traditionally adapted their learning designs based upon their local practice, this might be problematic when used in a distance learning setting, where content is offered by various educators in different local settings. In a recent special issue on learning design in this journal, Mor, Ferguson, and Wasson (2015, p222) suggest that 'teachers have the advantage of an intimate knowledge of the context of the learning and the characteristics of the learners, ensuring that they produce a design that is fit for purpose'. In order to 'scale up' this intimidate knowledge of the learning, 'research and practice in learning design aims to make the tacit practices of design for learning explicit, provide suitable textual, visual and computational representations to support these practices, and suitable tools to manipulate them and share them' (ibid) .

In this article we analyse the learning designs of courses studied by over 60000 students and make a first quantitative attempt at scrutinising these designs in order to better understand what activity types are used in different contexts, and how they relate to student outcomes. When educators have empirical evidence as to the impact of particular learning designs and / or student activities, they can use this information to improve course design and to share good practice across the institution.

While substantial progress has been made in the last 10 years in conceptualising learning design (e.g., Armellini & Aiyegbayo, 2010; MacLean & Scott, 2011) 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 the activity logs of students watching videos in online courses' (Mor et al., 2015, p222) is more informative when compared to the overall pedagogy and design of the course.

To the best of our knowledge, apart from our work (Rienties et al., 2012; Rienties, Toetenel, & Bryan, 2015) not a single study has compared how educators are making learning design decisions across a large number of modules. Building on our initial explorative study across 40 distance learning modules (Rienties et al., 2015) whereby learning designs significantly impacted on student behaviour and retention, in this article we will specifically focus on the core learning design processes by analysing and comparing the learning design decisions made amongst 157 blended and online modules at the Open University (OU). We will address the following two research questions:

1. To what extent are there common patterns in the way educators design a range of courses, including online and blended distance education modules?

2. What are the pedagogical implications for any patterns (or lack of these) and associated learning designs?

➔ Insert Practitioner notes about here

Setting

This study took place at The Open University, which is the largest higher education provider of distance education in Europe. Unlike traditional universities, the OU does not restrict enrolment on the basis of previous attainment, resulting in a widely varied learner population (Richardson, 2013). A new process for *mapping* modules (i.e. analysing and providing visualisations of module learning activities and resources) has been developed as part of a university-wide learning initiative (http://www.open.ac.uk/iet/learning-design/) which aims to use learning design data for quality enhancement.

Learning Design mapping

The OU learning design tools are developed using the taxonomy developed by Conole (2010). The tools are a combination of graphical, text-based tools that are used in conjunction with learning design activities, which are mandated at particular stages in the curriculum development process. Although a variety of factors are likely to impact on curriculum development, the outcomes of the decisions made by educators as a result of these factors are captured in the Learning Design visualisations.

In total 157 modules were mapped by the learning design team during the period January 2014-March 2015. For each module, the visualisation captured learning outcomes and categorised time planned on learning activities and total workload following the taxonomy in Table 1. Workload for this purpose is the number of hours that students are expected to study, which is difficult to measure as student start their learning journey at various different points and as a consequence, vary in the amount of time that they need to meet the assessed learning outcomes (Thorpe, 2006). Although the workload for individual students is likely to be different, it is important to estimate anticipated workload for the module as a whole as this has been ‘recognised as a major factor in the teaching and learning environment’ (Kyndt, Berghmans, Dochy, & Bulckens, 2014, p684). For example, if 120 out of 200 hours planned in a particular module are focused on assimilative activities, with the remaining activities focused on assessment, this was coded as 60% for assimilative and 40% for assessment, with the other five activities coded as 0% as displayed in Figure 1. It is important to note that the time that students spend on learning activities is defined and thus restricted based upon the size of the module, e.g. 30 credits equates to 300 hours of learning, whilst 60 credits equate to 600 hours of learning.

➔ Insert Figure 1 about here

➔ Insert Table 1 about here

Classifying learner activity can be subjective, and consistency is important when using data to compare module designs. The mapping process, used at the OU is intensive, typically taking between one to three days for a single module, depending on the number of credits, structure and quantity of learning resources. The learning design team held regular meetings to improve consistency across team members in the mapping process. For each module, the learning outcomes specified by the module team (pertaining to knowledge and understanding; cognitive skills; key skills; practical and/of professional skills) were captured by a learning design specialist. Each activity within the module's weeks, topics, or blocks was categorised according to the learning design taxonomy (see Table 1). These categorisations were captured in an "activity planner", sometimes referred to as pedagogy planner, a planning and design tool supporting the development, analysis and sharing of learning designs (Diego et al., 2008). Once the mapping process was completed by a learning design specialist, the learning design team manager reviewed the resulting module map 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 reviewed by at least three people, which enhanced the reliability and robustness of the data relating to each learning design. In some cases, the resulting module map was used for further analysis (outside the scope of this study) to undertake a thematic analysis of student comments captured as part of the end of module survey.

Results

Through retrospective mapping of student activity, using the Learning Design taxonomy in table 1, the Learning Design team produced an online data set which captured the Learning Designs for over 157 modules offered at the university, one of many data sets used the institution to evaluate its modules. By applying commonly used Learning Analytics techniques to this data set we set out to investigate patterns in the design decisions made and the impact of these on student outcomes.

We first considered common patterns in our data set, in accordance with RQ1: To what extent are there common patterns in the way educators design a range of courses, including online and blended distance education modules? Box plots, or box-whisker diagrams, visualise the median of the data set in relation to a box in which the middle 50% of the data falls, as illustrated in Figure 2. Visualisations of data are often easier to interpret than other statistical techniques, which is why these have been used. Figure 2 illustrates the range of seven learning design activities amongst 157 online and blended distance education modules, as well as the median of each respective activity, its whiskers and outliers. To take a metaphor, the box plot illustrates the frequency of learning design activities, like on a Walkman or HIFI-set, whereby module teams change the intensity of the levers to fit to the audience. As we are keen to explore both common and less common learning design patterns, we have kept the outliers in the subsequent analysis (even though the statistical results were not substantially different when outliers were excluded).

- ➔ Insert Figure 2 about here

On average, the most planned learning design activities consist of assimilative learning activities (M = 39.27, SD = 17.17), followed by assessment (M = 21.50, SD = 14.58). Assimilative activities include those in which students are asked to read learning materials, listen to audio clips, or watch videos. Reading, listening and watching are activities that are often associated with ways to provide information to students; a way to convey learning material from the educator to the student.

The categories of productive, communicative, finding information, experiental and interactive are relatively little used, as can be seen from their average use (productive (M = 13.13, SD= 10.40), communicative (M = 8.41, SD = 7.40), finding information (M = 6.76, SD = 7.08), experiential (M = 5.79, SD = 7.61) and interactive (M = 5.14, SD = 6.75)). These activities can all be said to be student activating, as they intend to use knowledge already gained in order to help students to make it their own. Productive activities ask students to produce an artefact, which could be a piece of writing or for instance a photo essay, depending on the subject area. Communicative activities ask students to engage with others in discussing the subject matter. Interactive/adaptive and experiential activities ask students to practically engage with the subject matter, in a real–life environment in the case of experiential activities, and in a simulated environment in the case of interactive/ adaptive tasks (see also Rienties et al. (2015)).

As displayed in the boxplot, several module team chairs did not use each of the seven learning design activities, in the order of non-usage: experiential (46%), interactive (43%), finding information (21%), communication (12%), productive (10%). So not all educators used all seven learning design activities at their disposal. Please note that we are not making any judgements about the appropriateness of these design decisions; indeed, modules without any experiential or interactive designs can equally lead to a rich or poor learning experience as modules with substantial experiential and interactive designs (Kirschner, Sweller, & Clark, 2006; Koedinger, Booth, & Klahr, 2013).

In order to further unpack whether common learning design patterns are present, we provide a correlation matrix in Table 2 of the seven learning design activities, total workload (in hours), level of study, and number of credits.

- ➔ Insert Table 2 about here

Assimilative activities are significantly negatively correlated to five of the six other learning design activities, indicating that educators chose assimilative activities over other learning design activities. Our findings suggest that many educators choose to convey information instead of using activities in which students use the information to communicate, produce or engage with information in a more practical manner.

Similarly, assessment activities are negatively correlated to all other learning design activities, with the exception of productive activities, indicating that similar choices are made between assessment activities and the other learning design activities. Again, this is an interesting finding, as often students are asked to demonstrate their understanding by producing an artefact, which is classed as productive activity or, when assessed, as an assessment activity.

However, in good practice in assessment, Tempelaar, Rienties, and Giesbers (2015) suggest that students should be given the opportunity to practice before they are assessed, which might explain the relationship between these two types of activities.

In contrast, student-activating learning design activities, such as finding information activities, are positively correlated with communication and experiential learning design activities. This seems to indicate that when educators design online courses whereby students are expected to search for additional sources, students are often asked to communicate this information with their peers or use this information in their own practice. In other words, when designing distance education modules educators are making significant decisions to include particular learning design activities at the expense of including other activities, in particular between assimilative, assessment, and student-activating learning design activities.

Our findings have established that, in particular, assimilative activities and assessment are most commonly used by educators, in order to unpack RQ2 we considered whether the level of study and number of credits might influence the choice of activity types. To do so, we investigated any variance between activity type, level and credits. So, as our second step, we used ANOVAs as illustrated in Figure 3, which show that the educational level has a strong significant impact on how educators design their modules, whereby at higher levels fewer assimilative activities are designed, from 42% in level 1 to 27% in postgraduate ($F = 6.801$, $p < .001$, $\eta^2 = .152$). At higher levels, educators seem to use more finding information ($F = 8.851$, $p < .001$, $\eta^2 = .189$), communication ($F = 2.947$, $p < .05$, $\eta^2 = .072$), and experiential learning design activities ($F = 2.667$, $p < .05$, $\eta^2 = .066$), in order to stimulate self-directed learning (Boyer, Edmondson, Artis, & Fleming, 2014).

→ Insert Figure 3 about here

As pointed out in Table 2, the number of credits (0, 15, 30, 60) given for a module is positively correlated with assessment, and negatively related to communication and interactive activities. While it makes intuitive sense that credit-bearing and high stake modules (e.g. mandatory modules or those with an exam to acquire professional accreditation) require students to spend more time on formative and summative assessment, it seems perhaps counter-intuitive that such modules have relatively few student-activating learning design activities.

Having established that both level and credit have an impact on the choice of learning activities, whilst keeping in mind that educators chose assimilative and assessment activities over the other five other Learning Design activity types, we considered whether there is a consequence to these pedagogical choices. In order to investigate the effect of these choices on student outcomes, we linked the learning designs with learning performance, as a final step. Table 3 below displays a correlation matrix of the seven learning design activities as well as learning performance.

→ Insert Table 3 about here

As most educators heavily rely on assimilative and assessment activities, we expected these types of activities to be positively related to student performance. We were surprised to find that six of the activity types in the Learning Design taxonomy were not significantly correlated with student performance. The only significant (negative) correlations between the seven learning design activities and learning performance appeared in relation to assimilative activities, suggesting that modules with a relatively high proportion of assimilative learning activities had significantly lower completion and pass rates than other modules. Although there are substantial variations in the module designs, our findings indicated that extensive reliance on assimilative activities seemed to have a negative influence on learning performance.

Discussion

By comparing and contrast 157 learning designs across a range of disciplines at one of the largest distance education universities, we found that educators use assimilative activities and assessment activities most in their Learning Designs. Assimilative activities are often used to convey information and thus is it not surprising to see them used widely, even though their effectiveness is debated for over forty years (Dale, 1970). As discussed earlier, the time that students spend on learning activities is defined and thus restricted based upon the size of the learning and thus the use of a particular learning activity precludes the use of another activities, as time can only be allocated once. As a result, many educators seem to rely heavily on assimilative and assessment activities, at the expense of other activities, namely student-activating activities in which students can use the knowledge acquired either to communicate, produce an artefact or apply their learning in a simulated or realistic environment. Interestingly, the balance of learning activities is influenced by credit and level, where Learning Designs at postgraduate level rely on fewer assimilative activities and the amount of time spent on assimilative increases almost proportionally as the level of study increases. Although assimilative and assessment activities are most commonly used by educators (Koedinger et al., 2013; Rienties et al., 2012), there is a wide variety of ways in which they are employed. Surprisingly, educators do not chose different activity types based upon function (e.g. replace one type of student-activating activity by another), but patterns can be seen where educators combine assimilative, productive and assessment activities or assimilative, finding & handling information and communication tasks. Whilst educators rely heavily on assimilative and assessment activities, no positive correlation was found between six of the seven Learning Design activity types and student outcomes. However, a negative correlation was found between an extensive use of assimilative activities and student outcomes, but further research is needed to ascertain the implications of this finding.

Conclusion

This study has taken a first step towards unpicking the various elements that are tacitly implicated in pedagogical decisions made by educators while designing their courses. To the best of our knowledge, this is the first study that has empirically investigated seven types of student activities, their distribution of use, and relationship with credit and level. We have taken a first step to link the elements of Learning Design to student performance, but further research is needed to unpack these elements further, building on the theoretical advances in Learning Design (Mor et al., 2015). Once we understand the pedagogical reasoning for decisions made (e.g. for particular credits or levels), and have a greater understanding of design challenges as well as key concepts and / or learning objectives, we can analyse these variables in conjunction with student outcome data. There might be other, more practical reasons such as administrative expectations for teacher assignments for instance, that impact pedagogical decision making too and these need further investigation. This more detailed analysis will help course design in the future, as by explicitly selecting a number of variables, predictions can be made as to the course's success. We need more institutions to make their Learning Design decisions explicit and to make data available, so that large multi-institutional studies can be undertaken to validate the findings of this study and ensure that these are generalizable (Arbaugh et al., 2008) across other institutions. This will help to empirically review the effect of pedagogical decisions made and measure their impact, supporting any Higher Education institution in improving students' success.

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Figures

Figure 1 Activity planner for Module X

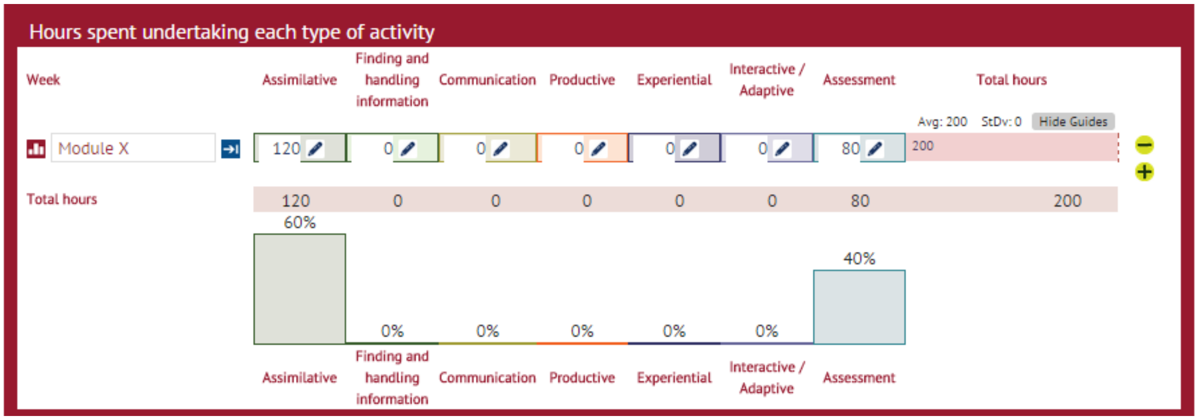


Figure 2 Boxplot of 157 learning designs (in percentages)

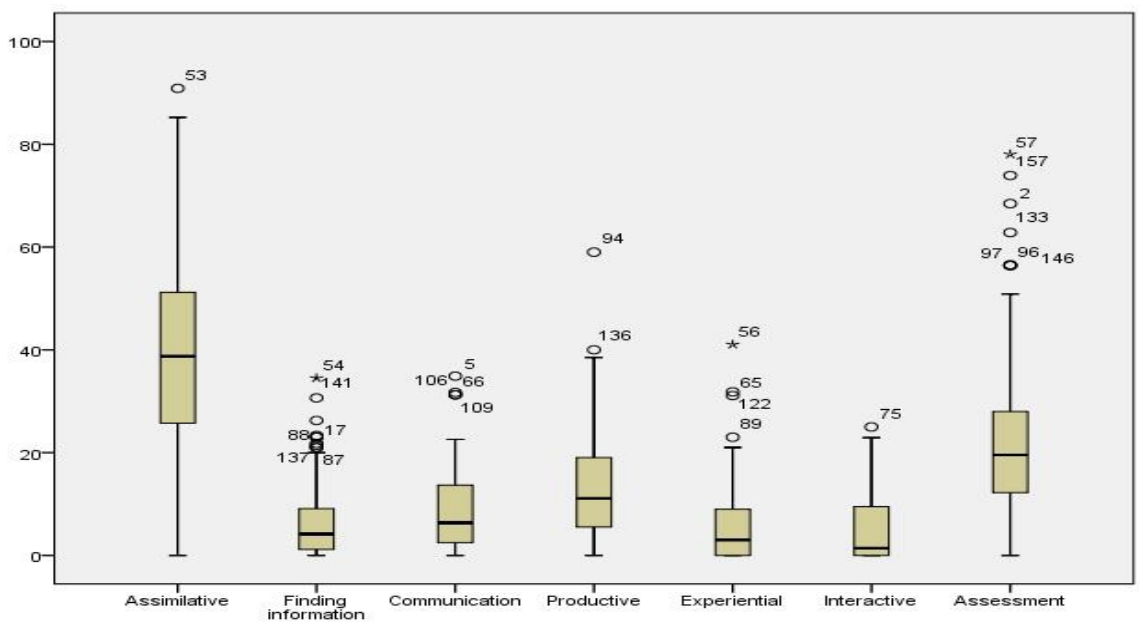
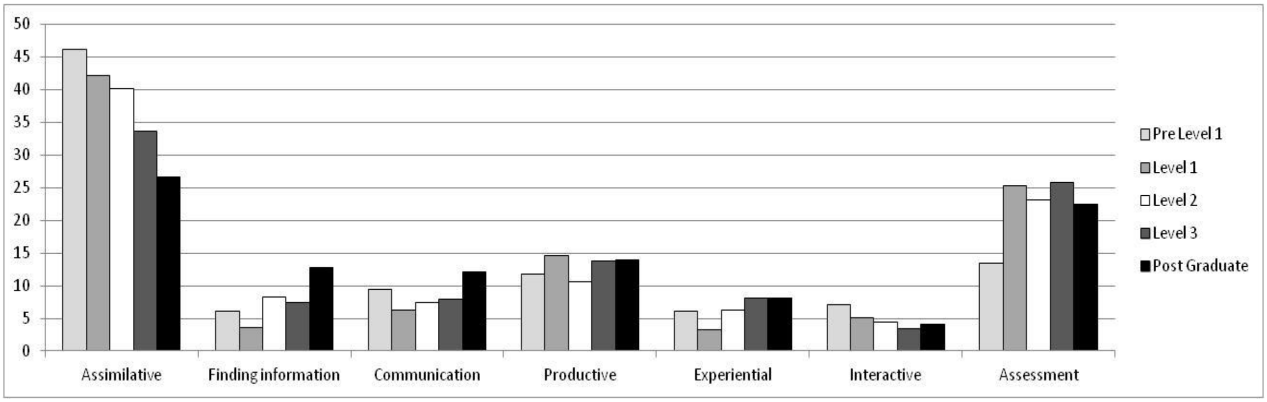


Figure 3 Learning design activities per level (in percentages)



*Pre-level 1 (n=41), Level 1 (n=50), Level 2 (n=20), Level 3 (n=21), Post-Graduate (n=25)

Tables

Table 1 Learning design taxonomy

	Assimilative	Finding and handling information	Communi-cation	Productive	Experiential	Interactive/ Adaptive	Assessment
Type of actvity	Attending to information	Searching for and processing information	Discussing module related content with at least one other person (student or tutor)	Actively constructing an artefact	Applying learning in a real-world setting	Applying learning in a simulated setting	All forms of assessment, whether continuous, end of module, or formative (assessment for learning)
Examples of activity	Read, Watch, Listen, Think about, Access, Observe, Review, Study	List, Analyse, Collate, Plot, Find, Discover, Access, Use, Gather, Order, Classify, Select, Assess, Manipulate	Communicate, Debate, Discuss, Argue, Share, Report, Collaborate, Present, Describe, Question	Create, Build, Make, Design, Construct, Contribute, Complete, Produce, Write, Draw, Refine, Compose, Synthesise, Remix	Practice, Apply, Mimic, Experience, Explore, Investigate, Perform, Engage	Explore, Experiment, Trial, Improve, Model, Simulate	Write, Present, Report, Demonstrate, Critique

Table 2 Correlation Matrix of learning design activities, level and credits

	M	SD	1	2	3	4	5	6	7	8	9
1. Assimilative	39.27	17.17									
2. Finding information	6.76	7.08	-.435**								
3. Communi-cation	8.41	7.40	-.362**	.372**							
4. Productive	13.13	10.40	-.297**	-.094	-.131						
5. Experiential	5.79	7.61	-.307**	.191*	.101	-.129					
6. Interactive	5.14	6.75	-.142	.056	-.005	-.096	.100				
7. Assessment	21.50	14.58	-.345**	-.221**	-.219**	-.140	-.259**	-.303**			
8. Workload	196.71	158.39	-.122	.155	-.138	.027	.163*	-.072	.067		
9. Level	1.61	1.41	-.383**	.340**	.122	.040	.158*	-.163*	.189*	.431**	
10. Credits	30.57	23.47	-.096	.081	-.223**	.010	.102	-.237**	.236**	.815**	.436**

*n = 157, Pearson Coefficient: **p* <.01, * p < 05.

Table 3 Correlation matrix of seven learning design activities and learning performance

	M	SD	1 Assimilative	2 Finding info	3 Communi-cation	4 Productive	5 Experiential	6 Interactive	7 Assessment	8 Total workload
Registrations	559.05	720.83	.286	-.027	-.196	.088	-.174	.032	-.203	-.022
Completed of Registered Starts	77.36	11.18	-.302	.046	.048	.269	-.018	-.178	.174	-.223
Passed of Completed	93.60	6.48	-.326*	.044	.017	.138	.159	.029	.148	-.262
Passed of Registered Starts	72.80	13.31	-.331*	.043	.035	.261	.037	-.136	.177	-.263

n = 40, * $p < .05$,