# Learning Analytics for Learning Design in Online Distance Learning

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There has been a growing interest in how teaching might be informed by *learning design* (LD), with a promising method for investigating LD being offered by the emerging field of *learning analytics* (LA). In this study, we used a novel LA for LD methodology to investigate the implementation of LD in an online distance learning context. A key innovation is the focus on *patterns* of LD. Using data from the virtual learning environment, outcomes data, and self-reports, for 47,784 students, we investigated the impact of those patterns on student behaviour, pass rates and satisfaction. A second innovation involves *social network analysis*. Our study revealed that different patterns of LD were associated with statistically significant differences in behaviour, but not in pass rates or satisfaction. Nonetheless, the study highlights that applying LA to LD might, in a virtuous circle, contribute to the validity and effectiveness of both, and to the enhancement of online distance learning.

**Keywords:** learning design; learning analytics; online distance learning; clustering; social network analysis

## Introduction

There has been a growing interest in how teaching, especially but not exclusively in online distance learning (ODL), might be informed by an approach known as *learning design* (LD)*:* "a methodology for enabling teachers/designers to make more informed decisions in how

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they go about designing learning activities and interventions" (Conole, 2012, p. 6). However, as is typical of an emerging field, there is already a complex array of competing yet overlapping approaches to LD and little consensus (Celik & Magoulas, 2016). Furthermore, if only because large-scale evaluations comparing different LD approaches can be difficult to achieve, which particular LDs are most effective in practice or have most potential remains unclear.

A promising method for investigating the efficacy of particular LDs is offered by a second emerging field, that of learning analytics (LA): "the measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environments in which it occurs" (Siemens, 2010, 6). Recent LA research (e.g., Mangaroska & Giannakos, 2018) has shown that LD has an important impact on students' learning behaviour, satisfaction, and outcomes.

In the study reported here, involving data for 47,784 students, we build upon that earlier research by using a novel LA for LD methodology to investigate the implementation of LD in an ODL context. A key innovation is the focus on combinations or patterns of LD activities, by means of a cluster analysis, rather than on individual LD activities, and the impact of those patterns on student behaviour in the virtual learning environment, pass rates, and satisfaction. A second innovation (building on, e.g., Haya, Daems, Malzahn, Castellanos, & Hoppe, 2015) involves applying a network analysis to the clusters, to further illuminate the relationships between learning activities within each cluster.

In addition to presenting our novel methodology and exploring its potential, we also critically appraise its implications for ODL, as exemplified in the United Kingdom's Open University (OU). In particular, we discuss how the application of LA to LD might, in a virtuous circle, contribute to the validity and effectiveness of both, leading towards the continuous enhancement of online distance and other approaches to learning.

The article continues with an introduction to LD, focusing on the context of ODL. Then, to illustrate the extensive variety of LD approaches, this is followed by a brief exploration of three LD approaches. Next, we introduce LA and the LA techniques used in our novel methodology, which is followed by the outcomes of applying that approach to the OU data. We conclude with a critical discussion of the methodology: its potential, its limitations, and its implications.

## LD

In the history of music there was a time long ago when some people argued it was impossible to write down music – music was too special, too ethereal – to ever be reduced to written form. However, over many years the Western music tradition slowly developed a notational system for describing and sharing musical ideas. This standard format allowed great musical ideas to be shared from one musician to another without a need for personal contact. (Dalziel et al., 2016, p. 2)

LD parallels this approach (the notation of musical compositions) enabling teachers and others to describe and share compositions or arrangements of learning activities so that they may be re-used or iteratively improved upon (Dobozy, 2013; Koedinger, Booth, & Klahr, 2013). This involves the selection, sequencing, and timing of specific learning activities, to constitute a learning episode, perhaps a single learning session or an entire course, whether face-to-face or online (although, for simplicity of exposition, hereafter we will refer only to learning modules, independent units of study that can be combined to form a university course). However, sometimes, LD goes beyond being a notational or descriptive framework. Some recognise that “different teaching approaches may be used for different subjects, and at different stages in learning” (Dalziel et al., 2016, p. 21), raising the possibility that effective LDs might be recommended for particular learning objectives.

LD emerged at least partly in reaction to *instructional design* (e.g., van Merriënboer & Kirschner, 2017), which focuses on one approach to teaching (instruction) rather than on the aim of the teaching (learning). Instructional design tends to adopt a predominantly content-centric approach to teaching and learning (Koper & Olivier, 2003) which, in the context of ODL (in which learners are independent in time and space, autonomous, self-regulated and self-directed), typically manifests as sequences of online resources. However, as has long been argued, “content transmission is not the only dimension of education” (Dalziel et al., 2016, p. 2). Instead, effective teaching and learning involves *active pedagogies* appropriate both to course objectives and to individual student motivations and skills, in order to enhance learning outcomes. In an ODL context, this involves leveraging the full affordances of the online interactive technologies, not just providing online access to books and videos. This is not to suggest that content is not important for learning (e.g., the learning of mathematics involves factual knowledge as well as procedural and conceptual knowledge, Delazer, 2003), but rather that a preoccupation with content (*knowing what*) should be moderated to accommodate a more robust understanding of effective learning experiences (which also involve *knowing how* and *knowing why*). In other words, rather than focusing on the process of instruction (with the teacher as provider of knowledge and the learner as recipient), LD draws on socio-constructivist theories of learning to emphasise the processes of, and the learner’s active role in, co-constructing meaning and learning.

**Approaches to LD**

Recent decades have seen significant work in LD, which has resulted in the complex array of approaches noted earlier. In particular, there have been multiple LD projects and initiatives, including the SoURCE project (Laurillard & McAndrew, 2001), the Art and Science of Learning Design workshop (Mor & Craft, 2012), and the Larnaca Declaration (Dalziel et al., 2016). Here, to illustrate the breadth of approaches, we will briefly discuss just three: the Learning Design Specification (IMS Global, 2003), the Learning Designer (Laurillard et al., 2013), and the Open University Learning Design Initiative (Cross, Galley, Brasher, & Weller, 2012).

### *IMS Global's Learning Design Specification*

IMS Global have authored a formal Learning Design Specification that separates learning content from learning opportunities in which that content might be made available (IMS Global, 2003). However, its emphasis nevertheless remains firmly on the content (albeit with the need for that content to be adaptable, reusable, shareable, interchangeable and machine-interpretable). More promisingly, although the framework is mainly instantiated in terms of resources, instructions, templates, and learning objectives, there is also some effort to ensure that it accommodates different kinds of approaches to pedagogy and assessment.

### *The Learning Designer*

A more nuanced and less content-centric approach to LD, grounded in Laurillard's *conversational framework* (1993), has been realised in an online interactive tool called the Learning Designer (Laurillard et al., 2013). In this approach, teaching and learning activities are categorised in terms of acquisition, inquiry, practice, production, discussion, and collaboration (see Table 1). The Learning Designer aims to facilitate the design of sequences of learning activities (such as reading texts, analysing data, practising exercises, producing videos, participating in discussion forums or collaborating in group projects) while accounting for specific properties (such as the activity's aims, outcomes, teaching methods, assessment, learning approach, duration, and necessary resources). However, the Learning Designer adopts a neutral position on what might constitute "good" LD in any specific context.

[TABLE 1 ABOUT HERE]

### *The Open University's Learning Design Initiative*

The OU has a team of LD specialists whose role is to advise course development teams on effective approaches to LD. The particular approach developed by the OU aims to focus on what students do as part of their learning, rather than on what teachers do. It emerged from the five-year JISC-sponsored Open University Learning Design Initiative (OULDI) (Cross et al., 2012), which involved consultation with eight other higher education institutions. This resulted in a comprehensive approach that includes a taxonomy of seven types of LD *activities* (see Table 2), module development teams participating in guided LD workshops, and an *activity planner* (a tool in which a module's activities and anticipated workloads are logged, in order to support the development, analysis, and sharing of LDs).

[TABLE 2 ABOUT HERE]

Although there are clear connections with the Learning Designer's learning types (Laurillard et al., 2013), the seven OULDI learning activities are categorised differently and have alternative emphases. *Assimilative activities* are defined as those in which learners attend to content. This includes reading course-related texts, watching course-related videos or listening to course-related audio files. *Finding and handling information* activities involve the student using sources such as the Internet, both to identify and to analyse information. *Communication* activities are defined as those in which students engage with another person (peer or tutor) about course-related content or issues. Meanwhile, *productive* activities draw upon constructionist models of learning and involve the building of course-related artefacts (e.g., a report, a video, or a presentation). *Experiential* activities are defined as those in which learners apply their learning in real-life or authentic settings, such as their workplace, and receive real life feedback from clients, colleagues or the environment, in order to facilitate skills transfer. *Interactive* activities have a similar ambition but involve simulations as proxies for situations that might have health, safety or access problems (e.g., inside a human heart or the rings of Saturn). Finally, *assessment* activities encompass all learning experiences focused on the various approaches to assessment.

**LA**

LA, which is both a field of enquiry and a set of computational approaches, involves the application of techniques from big data research (Mayer-Schonberger & Cukier, 2013), which aims to reveal insights that are otherwise hidden in complexity, to digital traces in educational contexts. Education has been generating big data (e.g., login, attendance, and achievement data) since the advent of learning management systems in the 1990s. This has accelerated with more recent virtual learning environments (VLEs) capable of recording almost every student interaction (including every mouse click and keyboard entry). This big educational data has led to the emergence of two complementary approaches – educational data mining (EDM, Baker, 2010) and LA (Ferguson, 2012), which are increasingly converging (du Boulay, Poulovassilis, Holmes, & Mavrikis, 2018). In particular, both are concerned with gathering, analysing in depth, and visualising interaction data obtained from digital learning environments, in order to provide actionable insight (Siemens, 2012) and to inform the improvement of teaching and learning. However, while EDM tends to focus on analytics for automatic adaption of educational software (e.g., Rummel et al., 2016), LA tends to focus on analytics and visualisations to enable teachers and students to do the adapting (Siemens, 2012).

Over recent years, a large body of literature has emerged around both conceptual development in LA (e.g. Clow, 2013) and how to design appropriate predictive LA to support students (e.g. Gašević, Dawson, & Siemens, 2015). For example, Lockyer, Heathcote, and Dawson (2013) have suggested two categories of LA applications (checkpoint analytics, to determine whether students have met the prerequisites for learning, and process analytics, to capture how learners undertake learning activities), while Bakharia et al. (2016) have proposed four types of LA (temporal, tool specific, cohort, and comparative).

**LA and LD**

As noted earlier, there has been a growing synergy between the two emerging fields LA and LD. Traditionally (e.g., Bennett, Agostinho, & Lockyer, 2015), the efficacy of LDs has been investigated using conventional education research techniques. However, these techniques present multiple challenges: observations are open to observer bias and are necessarily partial, self-reports are open to self-bias and can typically be collected only once the learning activity has finished, interviews are open to selection-bias and are limited to relatively small samples of participants, and student assessment outcomes only partially reflect the effectiveness of the learning activities. LA offers a complementary approach. By analysing actual student interactions in the form of trace data, LA has the potential to reveal unknown and unexpected patterns hidden in the resulting large data sets and may facilitate a relatively direct appraisal of the particular LD and its elements (e.g., Lockyer & Dawson, 2011; Persico & Pozzi, 2015), a possibility to which we return later. Meanwhile, as mentioned, one of the main challenges for LA research is to deliver actionable feedback, new knowledge that has a positive effect on future teaching and learning practices. This, it has been argued, is something that might be achieved by connecting the LA with pedagogy as manifested in LD, the context from which the learning data derives (Joksimović, Gašević, Loughin, Kovanović,

& Hatala, 2015; Rienties & Toetenel, 2016). Therefore, from both directions, there is increasing interest in aligning LA with LD: LA may facilitate making tacit LD practice explicit, while LD may provide educators with a pedagogical context for the interpretation of LA findings to support intervention.

Researchers at the OU have used LA techniques to investigate LD in a number of studies. For example, Rienties and Toetenel (2016) linked the LD of 151 modules with various markers of the behaviour of 111,256 students. They found that the LD strongly predicted VLE behaviour and student outcomes. For example, the LA revealed that the strongest predictor of student retention was the relative amount of communication activities. In a second study (Toetenel & Rienties, 2016a), this time investigating 157 OU modules, the researchers found that most modules included more assessment activities (e.g., tutor-marked assessments) and more assimilative activities (e.g., reading) than student-active activities (e.g., finding information). A third study (Toetenel & Rienties, 2016b) showed that LD analysis can be used to support the way in which modules are designed. When OU module writers were shown visualisations of their initial LD activities, they tended to adjust their designs towards more student-active activities (such as communication and finding information), reducing the emphasis on assimilative activities. A final example showed that LD could explain 69% of the variance in student VLE behaviour (Nguyen, Rienties, & Toetenel, 2017b), thus reinforcing the importance of LD.

As mentioned, key challenges faced by LA researchers include establishing a connection between LA and pedagogy (Wise & Shaffer, 2015). Without an approach firmly grounded in the learning sciences and educational practice, LA researchers cannot know what should be measured or which variables should be investigated. In any case, LA researchers can only measure that which can be measured; which is why, across the literature, easily quantifiable variables such as *time logged in* or *number of forum posts* are frequently used as proxies for intangible and complex cognitive states such as *engagement* (e.g., Nguyen, Rienties, Toetenel, Ferguson, & Whitelock, 2017). In turn, this might help explain why it can be difficult for researchers to translate LA findings effectively to LD in practice and to demonstrate that such application is effective.

However, there remains another possibility that has yet to be resolved. Perhaps the complexity of learning outcomes might be determined by patterns of LD activities, rather than individual LD activities, with each individual activity contributing to a small but critical multiplicative effect. This would be analogous to the way in which so-called polygenic biological human traits, such as hair colour or height, are determined by patterns of genes rather than individual genes and their interactions.

## LA and LD at the OU

### *Research questions*

As noted earlier, LD at the OU has been shown to emphasise assimilative and assessment activities (Nguyen et al., 2017b). Elsewhere, research using network analysis to investigate LD (Hora & Ferrare, 2013) has shown that educators tend to mix and match a wide variety of LD activities. Considered together, these findings raise an open question: do interactions between multiple LD activities (rather than, or in addition to, individual activities) have an important impact on student outcomes? This study first aimed to explore this question, in two steps, beginning with research question 1: What are common patterns of learning activities among 55 LDs?

Given the evidence that particular LD activities strongly influence student VLE behaviour, pass rates, and satisfaction (Rienties & Toetenel, 2016), the next step was to investigate the influence of any identified patterns of LD activities, suggesting research question 2: How do student behaviour, pass rates, and satisfaction vary across different patterns of LD activities?

### ***Participants***

Data was collated for 47,784 students (*M* = 868.80, *SD* = 886.90, per module) from 55 randomly selected OU modules for which data was available (i.e., this was a convenience sample of modules from across multiple domains). Of the sample, 57% self-identified as female and 43% male, while almost all of the participating students were from the United Kingdom (94%) and most declared their ethnicity to be "white" (87%). However, the participants varied markedly in age, with 21% under 25 years old, 34% aged 26–35, 22% aged 36–45, 14% aged 46–55, and 9% aged over 55. Around 70% of the participants were in work (51% full-time, 20% part-time); and around 31% of participants already had a degree or a postgraduate qualification, 38% had A levels or equivalent, while around 30% had neither A levels nor formal qualifications. A total of 9% of the participants reported a disability.

### ***Source data***

#### *LD data*

LD data (i.e., the constituent learning activities and their estimated duration) for each of the 55 modules were derived from the OULDI activity planner (which, as mentioned, is used to log the LD activities in each module).

#### *LA data*

LA data (student VLE interactions, student pass rates, and student satisfaction) were drawn from the institution's VLE (all OU students give consent for anonymised and aggregated data about their interactions with the OU's online systems to be analysed and reported in order to help the university improve its approaches) and from end-of-module surveys (for which again students give informed consent).

*Student VLE behaviour:* Following Nguyen et al. (2017), two types of VLE data were gathered per module as the only available proxies for student VLE behaviour: the average amount of time spent (in minutes) on the VLE per week and the average amount of time spent (in minutes) on the VLE per visit. These are inevitably crude measurements and, at best, represent only the average time a student spent logged into the VLE, not the actual time spent studying, and can be affected by unobservable factors. For example, time spent studying also often involves offline activities such as reading books, while time spent logged in can also involve the student not studying (e.g., being away from the computer or using alternative software such as social networks). Currently, neither of these potential confounds (offline studying and online not-studying) can be monitored nor accounted for.

*Student pass rates:* Student pass rates used in this study were calculated as the percentage of registered students who completed and passed the module (achieved at least the minimum acceptable mark specified by the university). This metric was chosen, rather than actual marks, to simplify the computations.

*Student satisfaction:* The OU regularly collects feedback (with informed consent) from students about their experience with the university, the aim being to improve its approaches to teaching and learning. The 40-item Student Experience on a Module survey, which is similar to other learner satisfaction instruments (Zerihun, Beishuizen, & Os, 2012), is sent to all students who are still registered at the end of the module. Here, we used the aggregate scores of five core items from the survey that have been shown to drive learner satisfaction

(Li, Marsh, Rienties, & Whitelock, 2017): teaching materials, assessment, advice and guidance, integration of materials, and career relevance.

## Analysis

### *Clustering networks of LDs*

An innovation of this study is that we formed clusters (identified patterns) of LDs, rather than focusing on individual types of learning activities in isolation. To form clusters based on multiple networks of learning activities, Quadratic Assignment Procedure (QAP) in UCINET was applied (Borgatti, Everett, & Johnson, 2018). QAP computes the Pearson correlation between all pairs of a set of equally sized square matrices, with the same actors (Hanneman & Riddle, 2005). The results of the QAP was a correlational matrix (55 rows x 55 columns) of the 55 LDs (from the study's 55 participating modules). Next, for bootstrapping, we applied 5000 permutations with a 21,463 random number seed, to compute whether or not a random measure is larger than or equal to the observed relations between the matrices (this bootstrapping procedure verifies whether the observed correlations are due to random chance). In the third step, we used an agglomerative hierarchical clustering technique with single-link method to identify clusters among the 55 LDs based on the measures of structural equivalence, with correlation as the measurement of similarity based on Euclidean distance (the higher the correlation, the more similar the two LDs). The last step was to use ANOVA to compare the different clusters according to student VLE behaviour, pass rates, and satisfaction.

### *Network analysis*

Following Nguyen et al. (2017b), and drawing on social network analysis techniques (Hanneman & Riddle, 2005), we employed network analysis to investigate the relationships between the seven OULDI activities, which involved quantifying and visualising the interactions and connections. The LD dataset was a weighted two-mode network, as illustrated in Figure 1.

[FIGURE 1 ABOUT HERE]

Since it was the relationships between the LD activities that was the main focus of the analysis, the Netdraw function of UCINET (Borgatti et al., 2002) was used to visualise the co-occurrences between each pair of LD activities across the five weeks. First, LD activities (the square nodes in Figure 1) are connected by edges (lines) to the module weeks (circular nodes) in which, according to the LD, they were present. Second, the weights of the connections, based on the workload (in hours per week) anticipated by the LD, are calculated and represented by the thickness of the edge (the thicker the edge, the higher the weighting and workload) and the numbers along each edge. Note that three of the seven LD activities do not appear in the network shown in Figure 1, either because according to the LD they were not present in any of the five weeks or because the workload (represented by the weighted edges) was negligible.

[FIGURE 2 ABOUT HERE]

Since the relationships among learning activities were the main focus, the dataset was next transformed to a one-mode network (Hora & Ferrare, 2013). For an illustrative example, see Figure 2, in which the thickness of the edges represents the weight between two LD activities (for clarity, numerical weightings are not displayed). Finally, as it can be argued that the connection between two LD activities is weaker when more LD activities are present, the weight of each edge was discounted by the number of LD activities in the same week (Newman, 2001). This can be generalised as follows:

$$w_{ij} = \sum\nolimits_p \frac{w_i p}{N_p - 1}$$

where $w_{ij}$ is the weight between LD i and LD j, and $N_p$ is the number of learning activities in week p.

## Results

### *Research question 1: What are common patterns of learning activities among 55 LDs?*

Using a 0.6 un-standardised correlation coefficient as a cut-off point yielded 6 clusters of modules with similar patterns of LD, illustrated by the dendogram in Figure 3: cluster 1 ($N$ = 2, $r$ = 0.60), cluster 2 ($N$ = 2, $r$ = 0.64), cluster 3 ($N$ = 2, $r$ = 0.70), cluster 4 ($N$ = 5, $r$ = 0.63), cluster 5 ($N$ = 12, $r$ = 0.72), and cluster 6 ($N$ = 32, $r$ = 0.64). It is important to highlight immediately that four of the clusters (clusters 1 to 4) only comprise very small numbers of LDs and so should be treated with caution. Further breakdowns of the relative frequencies of each type of LD activity by the six clusters are shown in Figure 4. At a glance, we can see that all clusters allocated most of their time for assimilative activities ($M$ = 49.04%, $SD$ = 12.90%) (e.g., reading texts or watching videos), followed by assessment activities ($M$ = 24.73%, $SD$ = 9.10%), and productive activities ($M$ = 16.05%, $SD$ = 11.53%). Only a small amount of the total workload was allocated for communication, experiential, or interactive activities.

[FIGURE 3 ABOUT HERE]

[FIGURE 4 ABOUT HERE]

A closer look at each cluster reveals that cluster 1 allocates the highest relative frequencies for assessment activities ($M$ = 37.39%, $SD$ = 10.39%) and the lowest for assimilative activities ($M$ = 29.51%, $SD$ = 10.39%), compared to other clusters. Cluster 1 also allocates a relatively high amount of time for communication and productive activities. Meanwhile, cluster 2 has the highest frequency for finding information ($M$ = 15.10%, $SD$ =

16.92%) and interactive activities (*M* = 29.38, *SD* = 28.10). Cluster 3 has the highest frequency of assimilative activities (60.51%, *SD* = 10.86%). Cluster 4 has a relatively high frequency of communication (*M* = 10.68%, *SD* = 7.68%) and productive activities (*M* = 20.25%, *SD* = 13.08%). Cluster 5 was highest in experiential activities (*M* = 4.25%, *SD* = 7.61%). Cluster 6, which is the largest cluster, allocates the majority of time for assimilative (*M* = 48.64%, *SD* = 12.45%), assessment (*M* = 23.99%, *SD* = 8.89%), and productive activities (*M* = 19.37%, *SD* = 11.69%), while ranking low in communication, experiential, interactive, and finding information activities.

The complexity of and differences between the LDs over time are illustrated by the longitudinal visualisations shown in Figure 5. This also reaffirms that, in line with Figure 3, the majority of LD activities in all six clusters were assimilative and assessment.

[FIGURE 5 ABOUT HERE]

[FIGURE 6 ABOUT HERE]

Figure 6 illustrates social network analyses of the different LDs by cluster. While, for visual clarity, the numerical weightings are not displayed, the thickness of the edges represents the strength of the connection (as before, the thicker the line, the stronger the connection). In Table 3, we also report the out-degree and in-degree as the total weights attached to the outgoing and incoming ties, respectively. These two measures represent the involvement of each node (i.e. each type of learning activity) in a network (i.e. a learning design). The higher the out-degree and in-degree are, the more involved a type of learning activity is. Since we are interested in comparing clusters, we took the average out-degree and in-degree per cluster.

[TABLE 3 ABOUT HERE]

Eyeballing the visualisations, it is evident that, across all the clusters, all of the strong connections involve assimilative activities. In cluster 1, assessment and assimilative activities are strongly connected (i.e., the activities frequently co-occurred in the modules), followed by assimilative and communication. In cluster 2, there are strong connections between assimilative and assessment, information, and communication activities. In this cluster, assessment and information activities are also strongly directly connected. Cluster 3 exhibits strong links between assimilative and communication activities and finding information activities. Clusters 4, 5, and 6 have a similar pattern, which indicates strong connections between assimilative, assessment, and productive activities. In cluster 4, communication activities are strongly connected to assimilative, assessment, and productive activities.

### *Research question 2: How do student VLE behaviour, pass rates, and satisfaction vary across different patterns of learning activities?*

#### *Student VLE behaviour*

Figure 7 illustrates the average time (in minutes) spent by students on the VLE per week ($M$ = 119.98, $SD$ = 89.47) and the average time (in minutes) spent on the VLE per visit ($M$ = 22.53, $SD$ = 9.05) sorted by the six clusters. Each module lasts for 30 weeks, and the VLE is open to the students for approximately three weeks before and after the module. A repeated measures ANOVA was used to compare the difference in student VLE behaviours across the six clusters. Overall, there were statistically significant differences across the six clusters in the time spent on the VLE per visit [$F(5,29) = 39.66$, $p < 0.01$)] and per week [$F(5,29) = 39.22$, $p < 0.01$)]. Post-hoc pairwise comparisons are shown in Table 4. For example, cluster 1 (which had the lowest frequency of assimilative activities) was associated with the largest amount of time spent in the VLE, while cluster 3 (which had the highest frequency of assimilative activities) was associated with the lowest amount of time in the VLE.

[FIGURE 7 ABOUT HERE]

[TABLE 4 ABOUT HERE]

*Pass rates*

Although the average pass rates in the clusters ranged from 45% to 88% ($M$ = 67%, $SD$ = 9%), a one-way ANOVA showed that the differences were not statistically significantly different ($F(5,47) = 1.83$, $p = 0.13$).

[FIGURE 8 ABOUT HERE]

Nonetheless, as shown in Figure 8, clusters 1, 2, and 4 had relatively high pass rates (above 75%), while the pass rates in clusters 5 and 6 varied notably across the different modules.

*Satisfaction*

A further one-way ANOVA showed that there were also no statistically significant differences in satisfaction across the six clusters [$F(4,45) = 1.34$, $p = 0.27$] (Figure 9). The average satisfaction score was 81% ($SD$ = 8%, ranging from 56% to 94%).

[FIGURE 9 ABOUT HERE]

**Discussion and conclusions**

This study employed a novel methodology which involved a combination of cluster analysis and network analysis to identify and interpret common patterns of LD activities across 55 LDs in an online distance learning institution. Our analysis identified 6 clusters of LD. However, as noted, the first important finding was that there were notable imbalances between these clusters, comprising a large difference in the number of LDs in each. In fact, in line with previous work (e.g., Nguyen, Rienties, & Toetenel, 2017a), the dominant cluster (cluster 6, $N$ = 32) focused on assimilative, assessment and productive LD activities. Our second largest cluster, cluster 5 ($N$ = 12), followed a similar pattern with the addition of some experiential activities. Accordingly, it might be the case that our analysis may have been overfitted to the data, a well-known big data issue that suggests patterns may have been found where there are none (Dietterich, 1995), which might be at least partially addressed by future LA research incorporating much larger numbers of LD.

Nonetheless, the methodology did identify a diverse range of inter-relationships between learning activities across the six clusters. In other words, even though most LDs in this study focused on assimilative activities (reading, watching, and listening), there were different combinations of LD activities across the different clusters. For example, assimilative activities were sometimes associated with communication activities (in clusters 1, 2, 3, and 4) and sometimes with assessment or productive activities (in clusters 4, 5, and 6). This warrants further research.

Our second finding, based on aggregated trace data of 47,000 students over the 30 weeks of the modules, indicated that the different clusters of LD activities were associated with statistically significant differences in the average time spent on the VLE per week and per visit. For example, cluster 1, with its emphasis on assessment and communication activities, had higher VLE interaction on average compared to the other clusters. Again, this is in line with previous findings (e.g., Nguyen et al., 2017b). It also reaffirms anecdotal observations that communication activities often depend on VLE tools, while preparing for assessment often involves students re-accessing the teaching materials via the VLE.

As has been mentioned, at The Open University considerable effort is invested in ensuring that module development teams have thoroughly considered (by means of workshops and further discussions) each of the seven LD activities and their sub-activities before deciding on what combination and balance might best support the students in that particular module. An aim of this study was to determine whether LA techniques might shed some relatively objective light on the combinations of LD, helping module teams to achieve combinations that are the most effective. However, the imbalance between the LD clusters identified in this study (ranging from Cluster 1 involving 2 LD and Cluster 6 involving 32

LD) (mainly due to the emphasis of OULDI LD on assimilative and assessment activities), together with the fact that there were no statistically significant differences in student pass rates or student satisfaction between the six clusters, only means that these remain open questions. In short, because the data focuses so heavily on assimilative LD activities, it remains unclear whether particular combinations of LD lead to better learning outcomes (which is, after all, the whole point of the LD). Accordingly, perhaps we need to include additional LDs (covering a wider range of disciplines, credits and level of study), in order to identify more robust LD clusters. In addition, perhaps our measures and granularity of student success (final pass rates, rather than weekly outcomes or raw marks) and student satisfaction are too crude and thus need to be reconsidered. Nonetheless, although again the imbalance between the clusters suggests caution, this finding does again warrant further research.

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While limiting our analysis and conclusions, the OU’s emphasis on more instructional activities (such as assimilation) does suggest that OU module designers may have found it challenging to move beyond (or have made an active choice not to move beyond) traditional instructional design approaches, to take on board the LD approach that has been promoted across the university. This highlights that, if LD is to be more successful across the OU and elsewhere, if it is to lead to better outcomes, more research needs to be conducted to demonstrate (if indeed it is true, which has not been confirmed by this particular study) that the more active LD activities ought to be prioritised. This would be a step change from the LD approaches advocated by OULDI (Cross et al., 2012) and by Laurillard's (2013) Learning Designer, as both of which LD are descriptive and neutral but not prescriptive. In other words, this study suggests that perhaps what is necessary are recommended clusters of LD, according to the learning objectives of the module designers.

Although the ambition to prioritise LD in course development is highly laudable, this study has also identified some other issues. To begin with, due to the OULDI's systematic comprehensiveness, active learning approaches that are well known to be effective, such as collaborative problem-solving (Luckin, Cukurova, Baines, Holmes, & Mann, 2017), only appear in the taxonomy as sub-activities within an activity, which might diminish their perceived importance. This also suggests a second closely related issue. The taxonomy does not prioritise any one sub-activity over any other sub-activity; all appear to be given equal weight, such that the imperative to achieve a good balance of activities can be interpreted as meaning achieving an equal weighting (in terms of time allocated to undertake each activity, Nguyen et al., 2017b). Presumably, an unintended consequence is that it is assumed that one seventh of study time should be spent in assimilative activities, one seventh in finding and handling information and so on (which is a naïve and unsubstantiated prescriptive approach to LD by the back door). However, there is as yet little evidence to suggest what is an effective balance of the various LD activities (although careful reflection suggests it is unlikely to be an equal time weighting of each across the module). Another issue, and this is a recurrent problem whenever a set of fluid concepts is nailed down in a taxonomy, is that there is the tendency for the taxonomy to become fixed and unchangeable, preventing the fundamental ideas developing or responding to changes in context or to developments in the learning sciences; for example, the OULDI taxonomy makes no mention of productive failure, which has been shown to be a particular effective LD in many circumstances (Kapur, 2008).

As we have noted, the LD data itself also raises a number of concerns. When using data to compare LD across disciplines and modules, it is important to classify LD activities as objectively and consistently as possible (Rienties & Toetenel, 2016). This is why the OU undertakes such a rigorous approach to the LD mapping. However, the current mapping process is labour-intensive and remains subject to individual and organisational bias, and the OULDI taxonomy inevitably over-simplifies the actual LD (keeping a taxonomy concise, in order to be able to generalise to other contexts, yet detailed, in order to separate different types of LD activities, remains a challenge). For example, multiple types of assessment (e.g., formative and summative) are collapsed into one category, while certain types of LD activities (especially communication activities) can be difficult to quantify (Rienties, Nguyen, Holmes, & Reedy, 2017). This, however, raises an interesting possibility. Perhaps LA, based on trace student VLE behavioural data, might provide educators and learning designers with a more realistic and more granular picture of how students actually spend time on certain learning activity, in contrast to the assumptions made in the mapping process. In other words, rather than using the LA to investigate patterns and outcomes of pre-specified LDs, the LA (perhaps in concert with a machine learning approach) might first be used to identify the actual LD that has been applied by the module designers before using that LD to investigate the student outcomes.

We should also, again, acknowledge the caveats of applying LA to VLE trace data. Although it might be argued that VLE trace data has contributed to an increased accuracy in predicting student outcomes, it does not capture student behaviour when offline (e.g., when reading books) and it might erroneously include time when the student is logged in but is not actively using the VLE (either they are not at their computer or they might be accessing other sites). A multimodal approach that captures and combines data from multiple perspectives might provide a more accurate picture of how students engage in their learning activities. However, this should be tempered with the acknowledgement that any outcomes depend on the data (which all too often is limited to the data that we can easily measure), its granularity, the proxies (e.g., equating logged in with engaged), and the analytical techniques that we employ.

The ambition of this study, to apply LA techniques to LD and VLE trace data in order to investigate the effect on learning of patterns of LD, to help unpack the complexity of LD practices and to empower learning designers to reflect upon and improve their own own LD in ODL institutions, is at least partly vindicated by the study’s outcomes. Although, our clusters were small, and most were focused on instructional design activities (such as assimilation and assessment), the study has reaffirmed the potential of using LA with LD, to make teaching practices explicit, sharable, and reusable. Simultaneously, it has also reaffirmed the importance of accounting for the pedagogical context in robust LA. Finally, the study has shown that applying LA to LD might contribute to the validity and effectiveness of both, in a virtuous circle, leading towards the continuous enhancement of online distance and other approaches to teaching and learning.

**Declarations of interest**

None.

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## TABLES

Table 1

*Types of Learning and Example Activities (adapted from Laurillard, 2013, p. 96)*

| **Learning through:** | **Example activities:** |
|---|---|
| Acquisition | • Reading books, papers or websites<br>• Listening to teacher presentations or lectures<br>• Watching demonstrations or videos |
| Inquiry | • Comparing texts<br>• Searching for information and ideas<br>• Analysing information and data |
| Practice | • Practising exercises<br>• Practice-based projects<br>• Labs or field trips<br>• Simulations and games |
| Production | • Producing essays, reports, designs, artefacts, models, videos, e-portfolios, blogs, performances... |
| Discussion | • Tutorials<br>• Seminars<br>• Study groups<br>• Online discussion forums or web conferences<br>• Social media discussions |
| Collaboration | • Group projects<br>• Building joint outputs (e.g., a wiki) |

Table 2

*Learning design taxonomy, adapted from ANONYMISED.*

| **Learning design activities** | **Description** | **Examples** |
|---|---|---|
| *Assimilative* | Attending to information. | Reading, watching, listening, thinking about, accessing. |
| *Finding and handling information* | Searching for and processing information. | Listing, analysing, collating, plotting, finding, discovering, using, gathering. |
| *Communication* | Discussing module related content with at least one other person (student or tutor). | Communicating, debating, discussing, arguing, sharing, reporting, collaborating, presenting, describing. |
| *Productive* | Actively constructing an artefact. | Creating, building, making, designing, constructing, contributing, completing. |
| *Experiential* | Applying learning in a real-world setting. | Practising, applying, mimicking, experiencing, exploring, investigating, |
| *Interactive/adaptive* | Applying learning in a simulated setting. | Exploring, experimenting, trialling, improving, modelling, simulating. |
| *Assessment* | All forms of assessment (summative, formative and self-assessment). | Writing, presenting, reporting, demonstrating, critiquing. |

Table 3

*Network metrics of clusters of learning design*

| | Cluster 1 | Cluster 2 | Cluster 3 | Cluster 4 | Cluster 5 | Cluster 6 |
|---|---|---|---|---|---|---|
| **Assimilative** | | | | | | |
| Out Degree | 68.56 | 109.60 | 123.74 | 102.90 | 121.47 | 97.07 |
| In Degree | 105.46 | 60.59 | 18.19 | 69.54 | 29.40 | 42.99 |
| **Assessment** | | | | | | |
| Out Degree | 90.81 | 41.81 | 12.50 | 26.12 | 27.12 | 20.83 |
| In Degree | 21.84 | 65.11 | 7.19 | 8.36 | 47.67 | 17.16 |
| **Productive** | | | | | | |
| Out Degree | 38.82 | 8.92 | 0.95 | 67.43 | 23.99 | 42.47 |
| In Degree | 32.49 | 20.02 | 4.06 | 59.95 | 54.33 | 65.04 |
| **Communication** | | | | | | |
| Out Degree | 27.96 | 11.42 | 19.15 | 40.67 | 2.03 | 5.20 |
| In Degree | 41.37 | 20.32 | 73.18 | 84.77 | 6.92 | 11.78 |
| **Information** | | | | | | |
| Out Degree | 11.22 | 37.89 | 6.20 | 10.77 | 3.93 | 6.67 |
| In Degree | 15.91 | 44.75 | 32.35 | 21.65 | 18.57 | 23.95 |
| **Experiential** | | | | | | |
| Out Degree | 2.75 | 3.17 | 5.88 | 0.17 | 8.94 | 2.73 |
| In Degree | 23.02 | 8.54 | 27.00 | 2.74 | 18.89 | 9.33 |
| **Interactive** | | | | | | |
| Out Degree | 0.00 | 29.38 | 4.98 | 0.48 | 4.51 | 3.77 |
| In Degree | 0.00 | 22.84 | 11.42 | 1.51 | 16.21 | 8.50 |

Note: Out Degree and In Degree were averaged per cluster

Table 4

*Tukey's HSD post-hoc pairwise comparison of VLE behaviour by cluster.*

| Time spent by students on the VLE per visit. | | | | | | |
|---|---|---|---|---|---|---|
| Cluster | Contrast | Std. Err. | t | P>t | [95% Conf. Interval] | |
| 2 vs 1 | -2.36 | 0.95 | -2.49 | 0.14 | -5.09 | 0.38 |
| 3 vs 1 | -11.13 | 0.99 | -11.24 | 0.00 | -13.99 | -8.27 |
| 4 vs 1 | -0.23 | 0.95 | -0.24 | 1.00 | -2.97 | 2.51 |
| 5 vs 1 | -5.46 | 0.95 | -5.76 | 0.00 | -8.20 | -2.72 |
| 6 vs 1 | -5.67 | 0.95 | -5.99 | 0.00 | -8.41 | -2.94 |
| 3 vs 2 | -8.77 | 0.99 | -8.86 | 0.00 | -11.63 | -5.91 |
| 4 vs 2 | 2.12 | 0.95 | 2.24 | 0.23 | -0.61 | 4.86 |
| 5 vs 2 | -3.10 | 0.95 | -3.28 | 0.02 | -5.84 | -0.37 |
| 6 vs 2 | -3.32 | 0.95 | -3.5 | 0.01 | -6.06 | -0.58 |
| 4 vs 3 | 10.89 | 0.99 | 11 | 0.00 | 8.03 | 13.76 |
| 5 vs 3 | 5.67 | 0.99 | 5.72 | 0.00 | 2.81 | 8.53 |
| 6 vs 3 | 5.45 | 0.99 | 5.51 | 0.00 | 2.59 | 8.31 |
| 5 vs 4 | -5.23 | 0.95 | -5.52 | 0.00 | -7.96 | -2.49 |
| 6 vs 4 | -5.44 | 0.95 | -5.74 | 0.00 | -8.18 | -2.71 |
| 6 vs 5 | -0.22 | 0.95 | -0.23 | 1.00 | -2.95 | 2.52 |

| Time spent by students on the VLE per week. | | | | | | |
|---|---|---|---|---|---|---|
| Cluster | Contrast | Std. Err. | t | P>t | [95% Conf. Interval] | |
| 2 vs 1 | 7.55 | 9.58 | 0.79 | 0.97 | -20.12 | 35.22 |
| 3 vs 1 | -63.88 | 9.96 | -6.41 | 0.00 | -92.67 | -35.10 |
| 4 vs 1 | 23.88 | 9.58 | 2.49 | 0.13 | -3.79 | 51.55 |
| 5 vs 1 | -17.32 | 9.58 | -1.81 | 0.46 | -44.99 | 10.35 |
| 6 vs 1 | -10.73 | 9.58 | -1.12 | 0.87 | -38.41 | 16.94 |
| 3 vs 2 | -71.43 | 9.80 | -7.29 | 0.00 | -99.75 | -43.11 |
| 4 vs 2 | 16.34 | 9.37 | 1.74 | 0.51 | -10.75 | 43.42 |
| 5 vs 2 | -24.87 | 9.37 | -2.65 | 0.09 | -51.95 | 2.22 |
| 6 vs 2 | -18.28 | 9.37 | -1.95 | 0.38 | -45.37 | 8.80 |
| 4 vs 3 | 87.77 | 9.80 | 8.96 | 0.00 | 59.45 | 116.09 |
| 5 vs 3 | 46.56 | 9.80 | 4.75 | 0.00 | 18.25 | 74.88 |
| 6 vs 3 | 53.15 | 9.80 | 5.42 | 0.00 | 24.83 | 81.47 |
| 5 vs 4 | -41.20 | 9.37 | -4.40 | 0.00 | -68.29 | -14.12 |
| 6 vs 4 | -34.62 | 9.37 | -3.69 | 0.00 | -61.70 | -7.53 |
| 6 vs 5 | 6.59 | 9.37 | 0.70 | 0.98 | -20.50 | 33.67 |

**FIGURES**

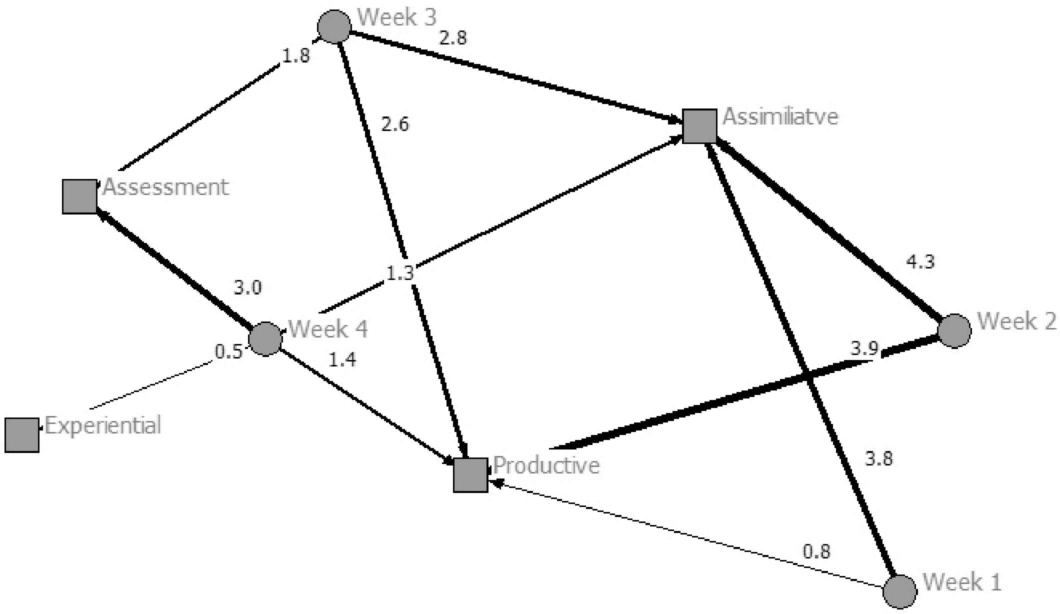


*Figure 1.* Weighted two-mode network of a module (including, for visual clarity, data from only the first five weeks.

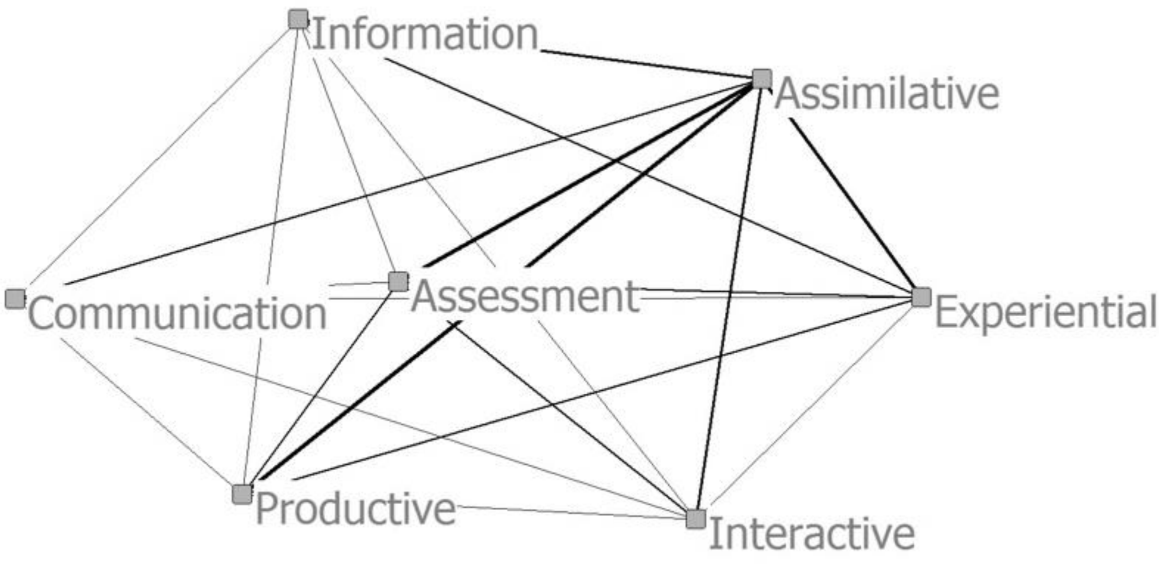


*Figure 2.* Example one-mode network across 30 weeks for a sub-set (for visual clarity) of the 55 modules.

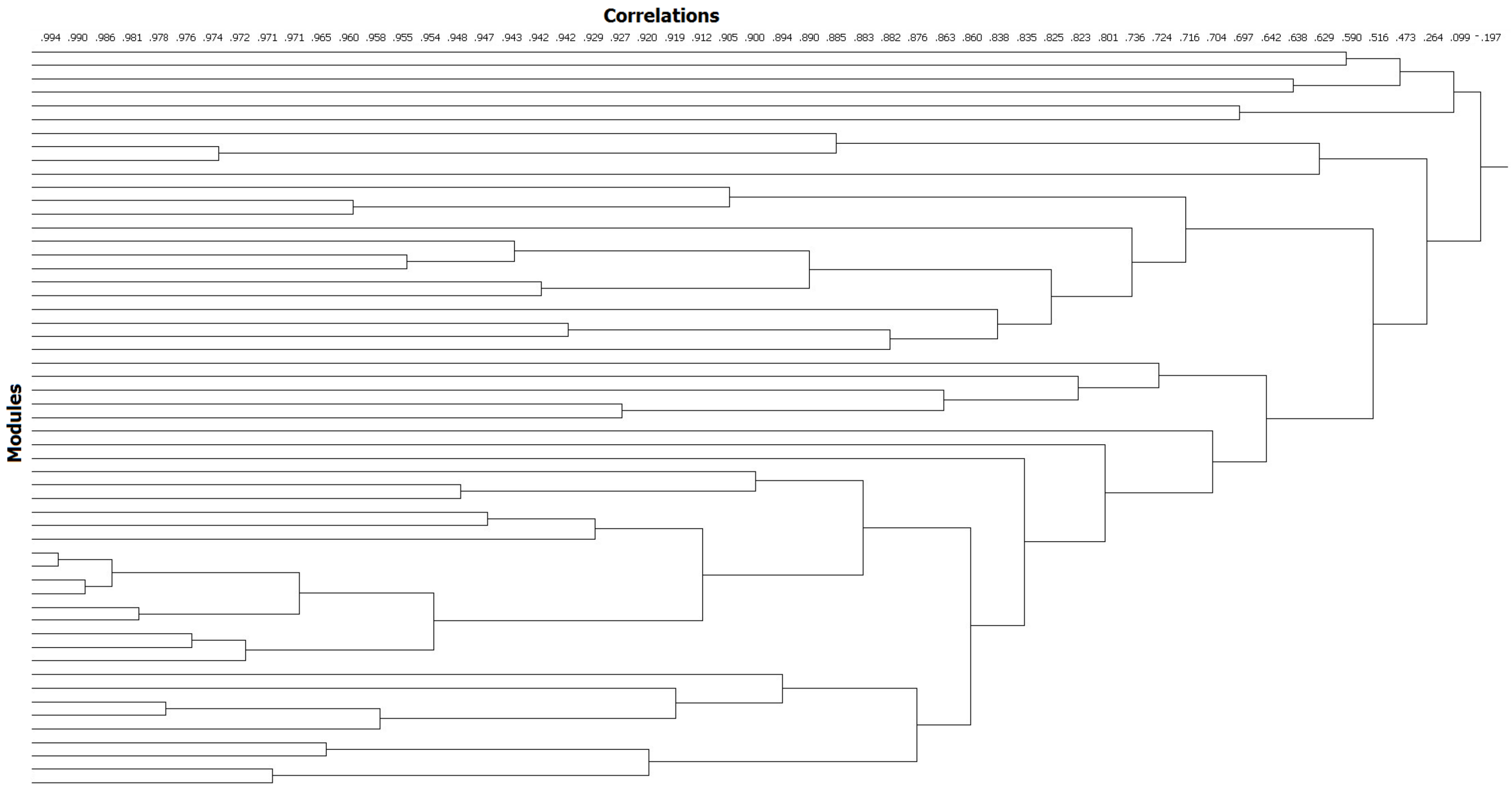


*Figure 3.* An illustrative dendrogram clustering the 55 learning designs.

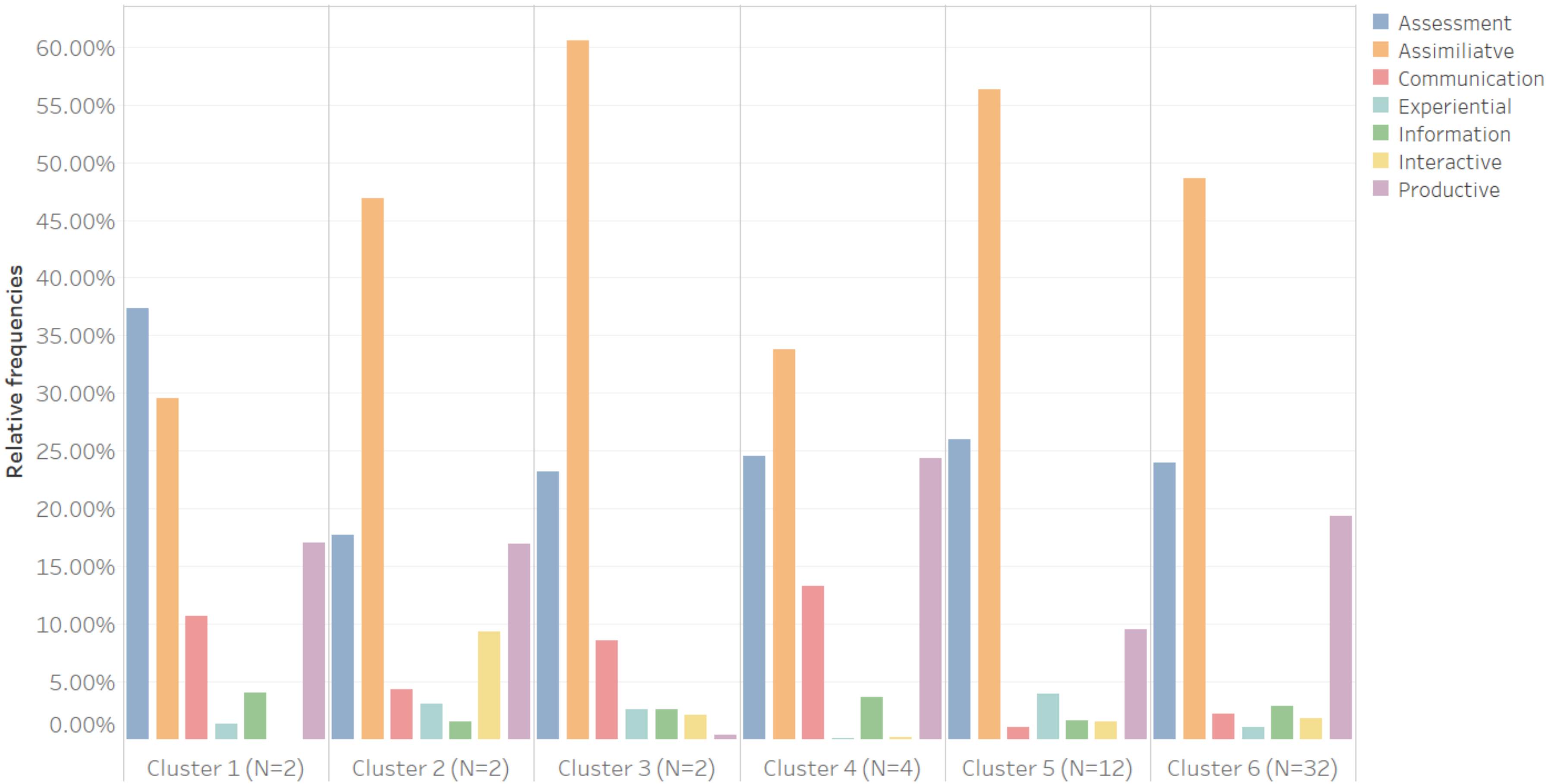


*Figure 4.* Clusters of learning activities among 55 learning designs.

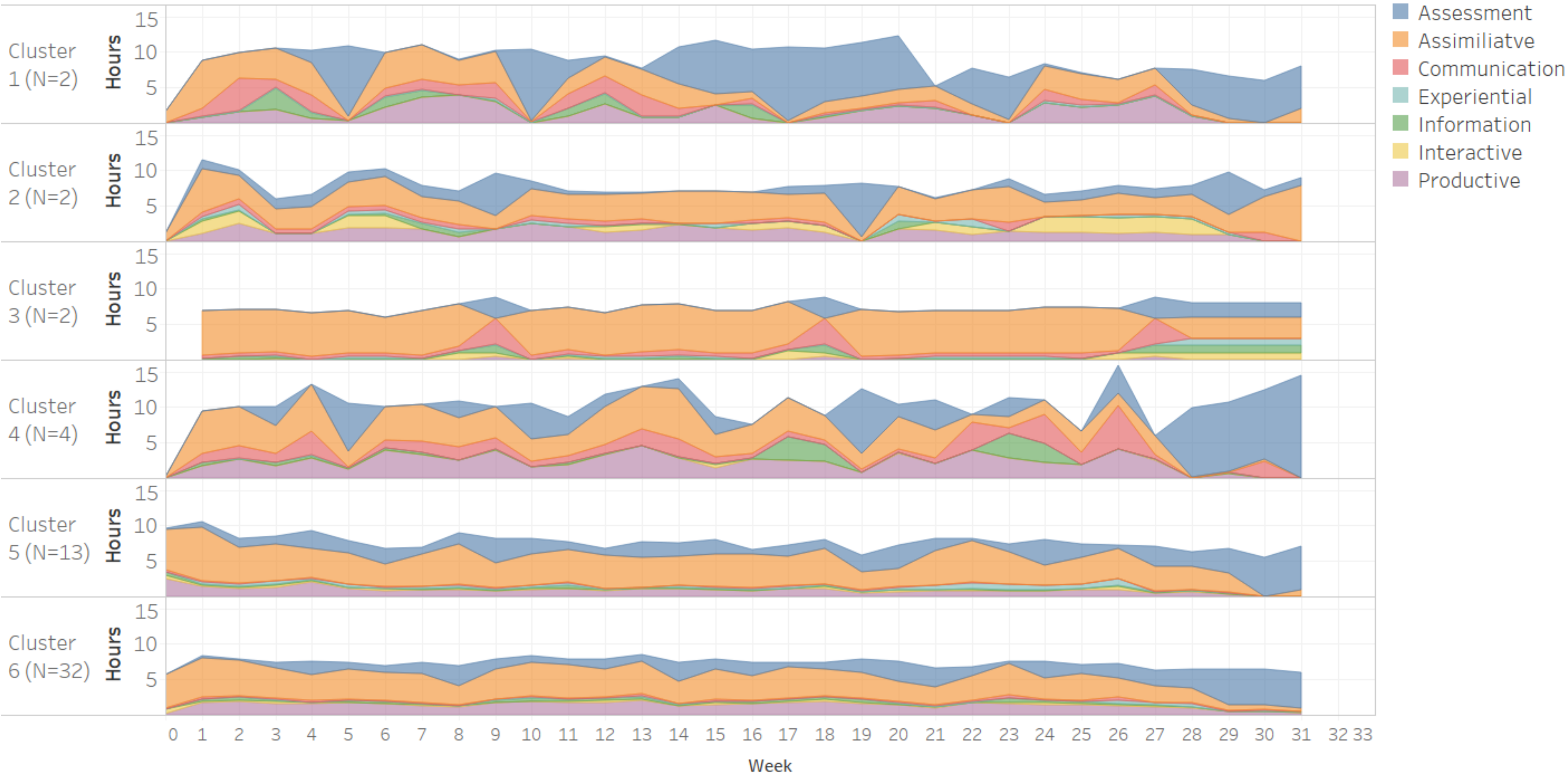


*Figure 5.* Longitudinal visualisation of learning designs over 30 weeks by clusters.

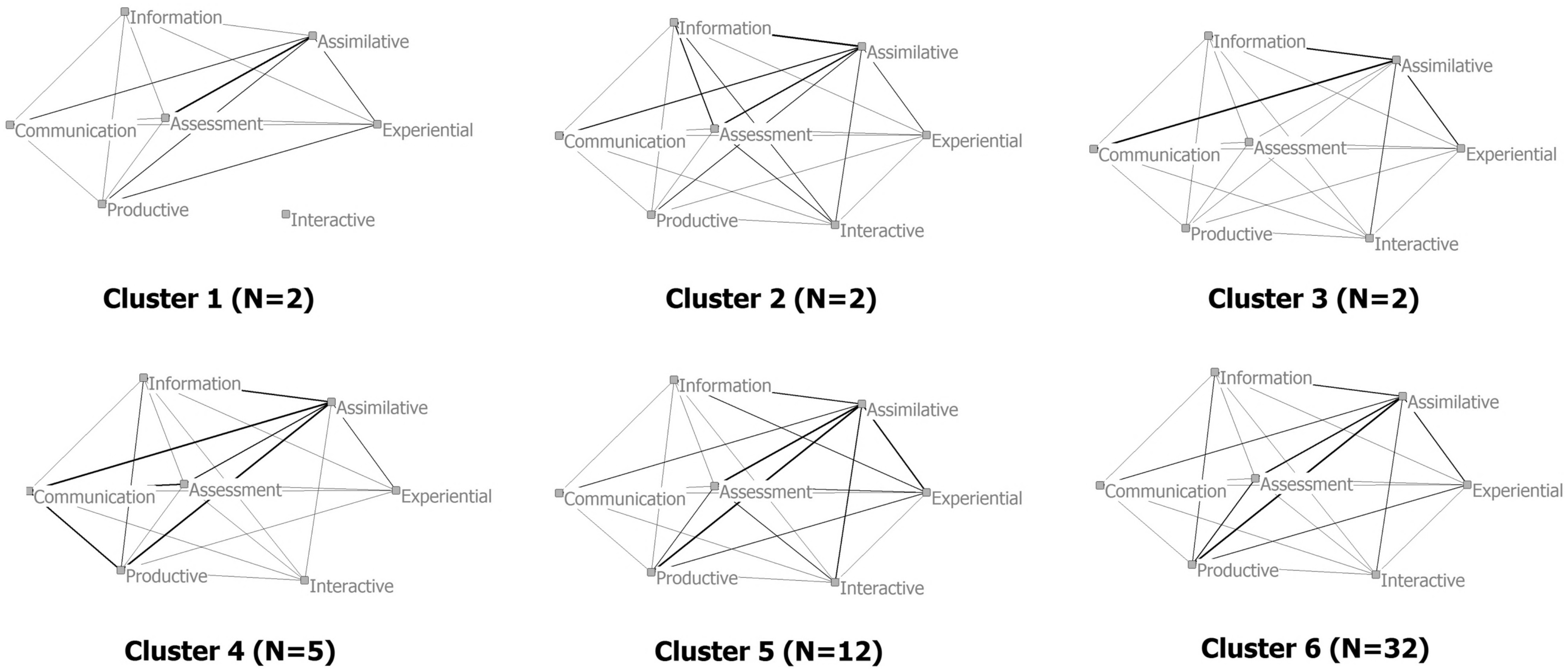


*Figure 6.* Overlapped networks of learning designs by clusters.

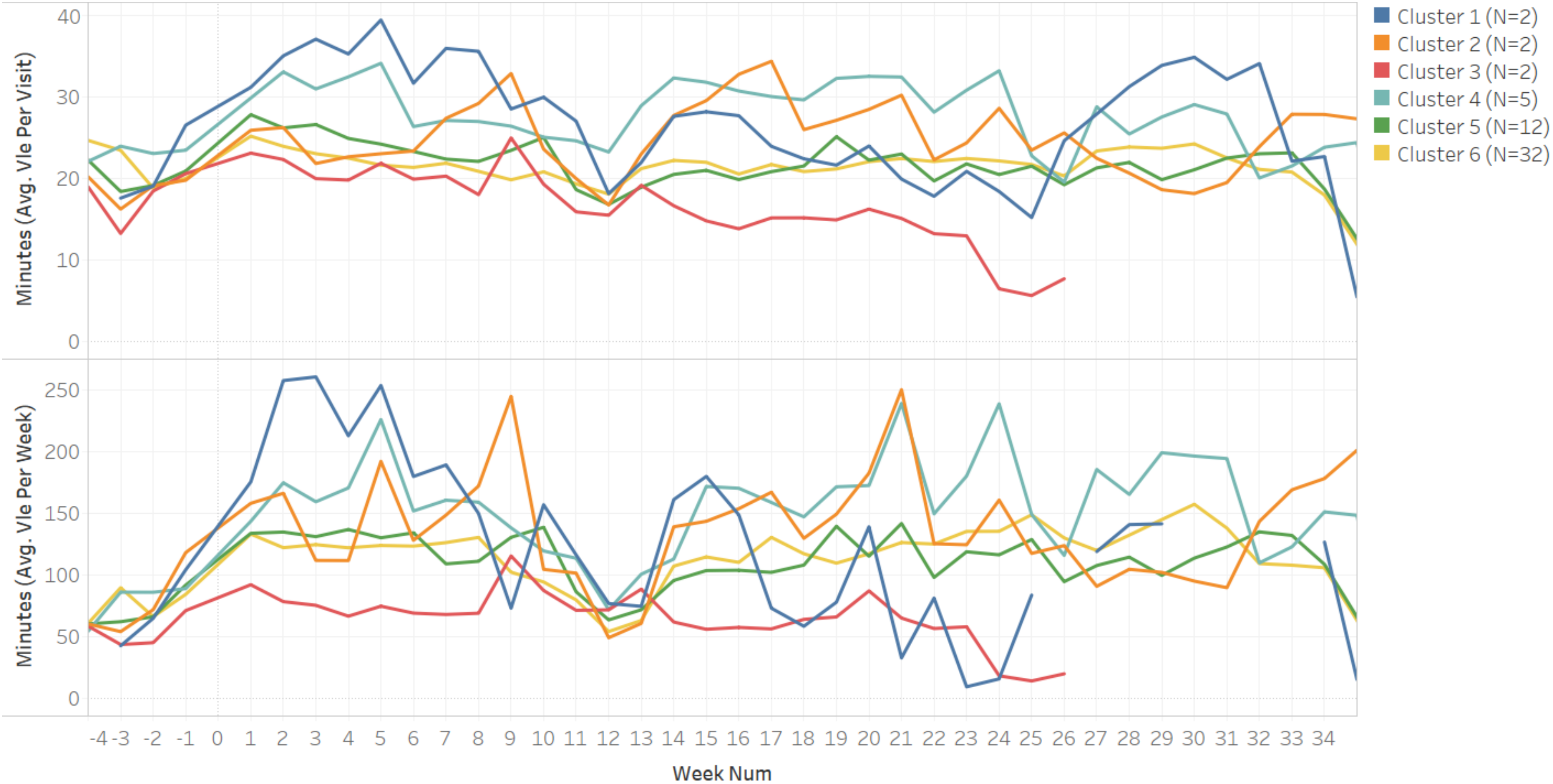


*Figure 7.* VLE activities over 30 weeks by cluster.

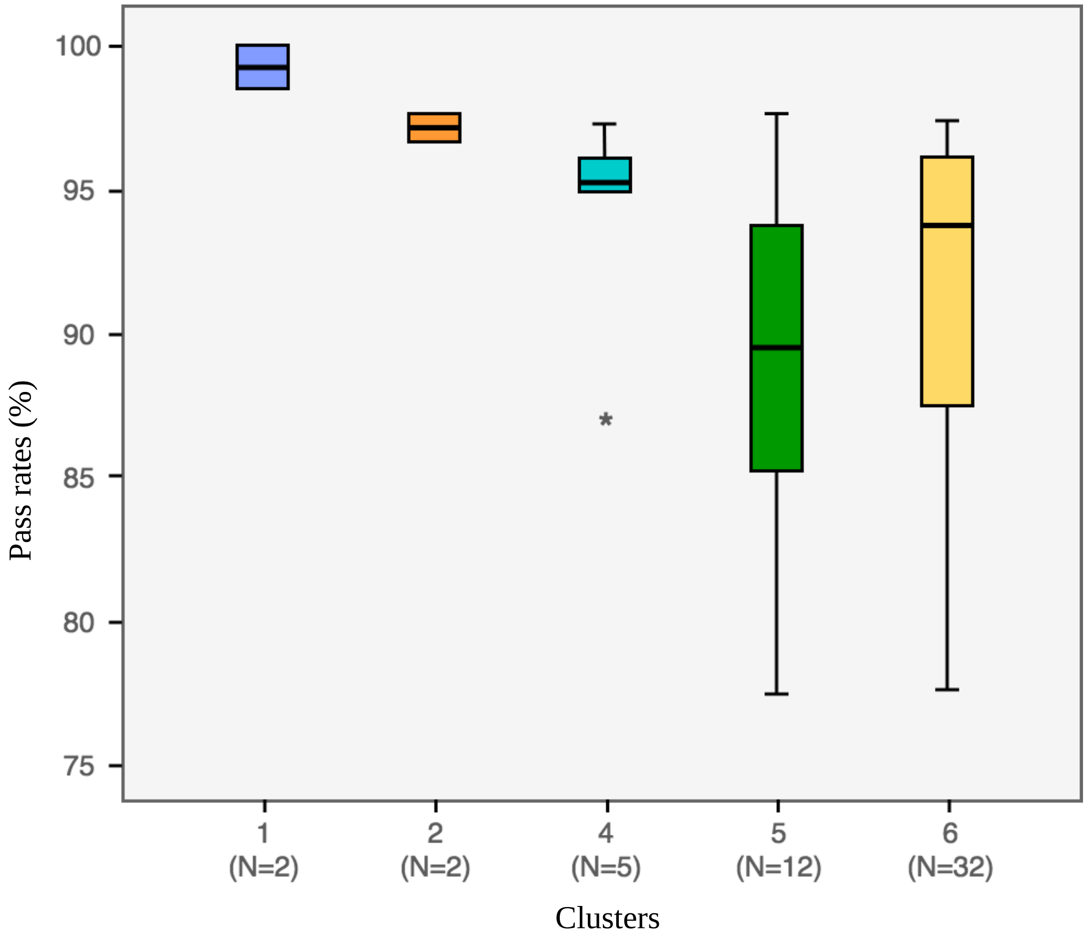


*Figure 8.* Pass rates by cluster (NB Cluster 3 does not appear because of insufficient data).

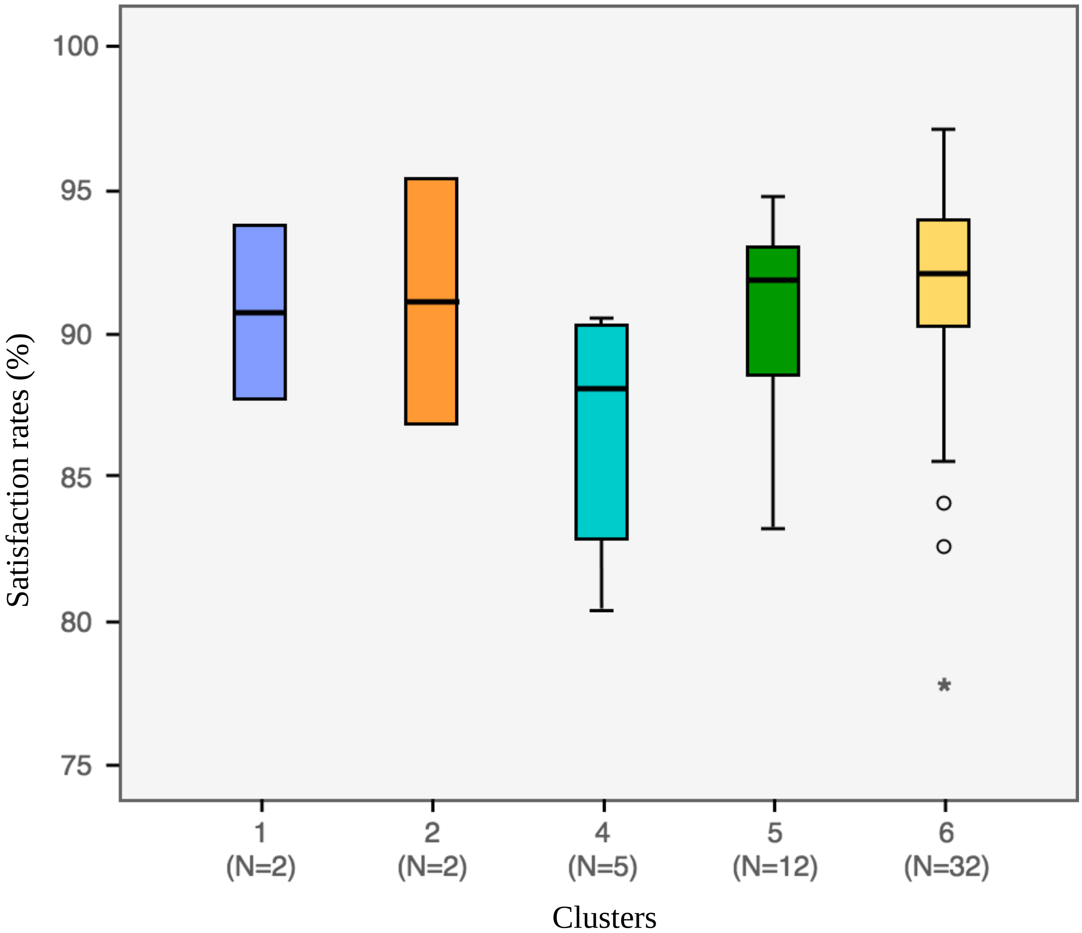


*Figure 9.* Satisfaction rates by cluster (NB Cluster 3 does not appear because of insufficient data).