Unravelling the Temporal Process of Learning Design and Student Engagement in Distance Education using Learning Analytics

Thesis

Unravelling the temporal process of learning design and student engagement in distance education using learning analytics

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Abstract

Designing a curriculum in online and distance education can be challenging because the processes of what, when, and how students study are not always visible to teachers due to the limited opportunities for face-to-face interactions. The aim of this thesis is to explore how teachers design for learning, together with how the learning design impacts upon the students' actual engagement with the learning materials, with the subsequent effect on their academic performance. One way forward, is to build on the intersection between the most recent work in learning analytics and learning design research. I have therefore argued for and investigated the potential of incorporating the design of learning activities into the analysis of student learning behaviour. On the one hand, the visualisation of learning activities designed by teachers provides the pedagogical context to improve the interpretation of the observed learning behaviour and its effect on academic performance. On the other hand, the analysis of online digital traces of learning activities offers a dynamic account of how students learn in practice in a distance learning environment. As a result, this thesis sheds new light on the implicit process of how learning design influences student engagement in distance education

By employing a mixed-method research design, I first examined how teachers design for learning using visualisations and network analysis of 37 modules over 30 weeks at The Open University. In the next step, I conducted an in-depth qualitative investigation with 12 teachers into the underlying factors that influenced their design decisions, as well as the perceived barriers and affordances of adopting approaches from the Open University Learning Design Initiative. The findings revealed common patterns as well as variations in learning design across modules and their disciplines of study. Analysis of the interviews revealed underlying tensions between teachers' autonomy and the influence of management and institutional policies in the design process and the adoption of learning design tools.

After laying out the foundation for understanding the learning design processes, I carried out a large-scale analysis of 37 modules and 45,190 students to examine how learning design influences student engagement, satisfaction, and performance. The findings indicated that learning design explained up to 69% of the variance in student engagement, which was strongly driven by assimilative, assessment, and communication activities. Finally, I conducted a fine-grained analysis exploring the (in)consistencies between learning design and student behaviour and how different engagement patterns impact academic performance. The analysis found misalignments between how teachers designed for learning and how students actually studied. In most weeks, students spent less time studying the assigned materials compared to the number of hours recommended

by instructors. High-performing students not only studied ‘harder’ by spending more time, but also ‘smarter’ by engaging in a timely manner.

Altogether, this thesis has contributed new scientific insights into the dynamic temporal aspects of how teachers design for learning and the relations between learning design, engagement, and academic performance in distance education. As an implication, the findings reported here demonstrated how learning design could improve the accuracy and interpretability of learning analytics models, and how learning analytics could help teachers identify potential inconsistencies between learning design and student behaviour.

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This thesis marks the end an important chapter in my adulthood and the beginning of a new one with many exciting opportunities for me to pursue my passion for research. I am looking forward to what lies ahead.

Declaration of Authorship

I declare that this thesis has been composed solely by myself and that it has not been submitted, either in whole or in part, in any previous application for a degree. Except where otherwise acknowledged, the work presented is entirely my own. Much of the empirical research outlined in this thesis has been published in peer-reviewed conference proceedings and journals. Appropriate citations are given to such work throughout. No publications are given in their entirety or in place of particular chapters. However, portions of the publications are adapted within the narrative, particularly in the analysis chapters (Chapter 4 to Chapter 7).

References to Relevant Work

The empirical work in Chapter 4 has been published as:

- **Nguyen, Q.,** Rienties, B., & Toetenel, L. (2017). Unravelling the dynamics of instructional practice: a longitudinal study on learning design and VLE activities. *In Proceedings of the 7th International Learning Analytics & Knowledge Conference (LAK17)*, Vancouver, Canada, ACM, New York, NY, USA, 168–177.
- **Nguyen, Q**., Rienties, B., & Toetenel, L. (2017). Mixing and matching learning design and learning analytics **(best paper award).** In P. Zaphiris & A. Ioannou (Eds.), *Learning and Collaboration Technologies: Fourth International Conference, LCT 2017, Part II, Held as Part of HCI International 2017, Proceedings* (Vol. 10296, pp. 1-15). Springer International Publisher.

The empirical work in Chapter 6 has been published as:

- **Nguyen, Q.**, Rienties, B., Toetenel, L., Ferguson, R., & Whitelock, D. (2017). Examining the designs of computer-based assessment and its impact on student engagement, satisfaction, and pass rates. *Computers in Human Behavior, 76*, 703-714.

The empirical work in Chapter 7 has been published as:

- **Nguyen, Q.**, Huptych, M., & Rienties, B. (2018). Linking students' timing of engagement to learning design and academic performance **(best full paper award)**. *In Proceedings of the 8th International Learning Analytics & Knowledge Conference (LAK18)*, Sydney, Australia, ACM, New York, NY, USA, 141-150.
- **Nguyen, Q.**, Huptych, M., & Rienties, B. (2018). Using Temporal Analytics to Detect Inconsistencies between Learning Design and Student Behaviours. *Journal of Learning Analytics, 5*(3), 120-135.

Table of Contents

List of Figures

List of Tables

List of abbreviations

LD – Learning design

LA – Learning analytics

VLE – Virtual learning environment

LMS – Learning management system

OU – Open University UK

SEaM surveys - Student Experience on a Module surveys

TMA – Tutor marked assessment

EMA – End of module assessment

OULDI – Open University Learning Design Initiative

TEL – Technology Enhanced Learning

LTI – Learning and Teaching Innovation

AL – Associate Lecturer

Chapter 1 – Introduction

Nowadays, teaching is just no longer about delivering information, but about planning and designing learning activities, resources, and technologies to help students achieve their goals (Goodyear, 2015; Kirschner, 2015; Paniagua et al., 2018; Persico et al., 2018). Teachers are expected to not only have a deep understanding of what they teach but also whom they teach and how they teach. That entails designing an effective curriculum, using technologies to support learning activities and creating engaging lessons that meet the diverse needs of students and institutions. In the UK, teaching effectiveness is often evaluated through course evaluations such as the National Student Survey and retention rates (i.e., how many students continue their studies from one year to the next) (Gunn, 2018). However, there are concerns about whether these metrics can empower teachers to improve their teaching practices, or whether they primarily serve the purposes of quality control for institutions and government (Hornstein, 2017; Neary, 2016). While course evaluations and retention rates are related to learning outcomes to some extent, they give limited insights into the learning process and questions of what, when, why, and how students learn. Understanding these learning processes is even more challenging in online and distance education due to the lack of face-to-face interactions between teachers and students.

Since the early 2000s, two strands of research in education have emerged that can help educators gain better insights into the teaching and learning process. These are learning design (LD) and learning analytics (LA). Learning design, in this context, is defined as "*a descriptive framework for teaching and learning activities ("educational notation"), and to explore how this framework can assist educators to share and adopt great teaching ideas*." (Dalziel et al., 2016, p.4). Research in LD has developed a wide range of tools and frameworks to document and visualise sequences of learning activities designed by teachers and to guide them through the LD process (AUTCLearningDesign, 2002; Cross et al., 2012; Dalziel, 2003; Hernández-Leo et al., 2018; Koper et al., 2004; Laurillard et al., 2018; McAndrew et al., 2006). Through the transition from implicit to explicit representations of LD, teachers can reflect on their practices, while re-using and adapting good instructional approaches from others (Agostinho et al., 2011).

In parallel to LD, LA has emerged as a field in the decade since the first Learning Analytics Knowledge (LAK) conference in 2011. Learning analytics is defined as "*the measurement, collection, analysis and reporting of data about students and their contexts, for purposes of understanding and optimising learning and the environments in which it occurs*" (Ferguson, 2012, p.305). LA research typically collects a large amount of data about students such as demographics, course performance, activity logs of students (Macfadyen et al., 2010), discussion forums interactions (Bakharia et al., 2011; Wise et al., 2017), and open texts from essays or course evaluations (Ullmann, 2019; Whitelock, Twiner, et al., 2015). By taking advantage of advanced analytical techniques such as machine learning (Ullmann, 2019), text-mining (Whitelock, Twiner, et al., 2015), and social network analysis (Wise et al., 2017), LA has created practical applications to support the learning process. One example is to improve retention rates through interventions based on predictions of students at risk of falling behind using student historical data (Arnold et al., 2012; Kuzilek et al., 2015; McKay et al., 2012).

Although LA and LD had two different origins, there exists a strong synergy between the two fields, which was acknowledged at the first LAK conference (Lockyer et al., 2011) and in subsequent discussions (Bakharia et al., 2016; Griffiths, 2017; Lockyer et al., 2013; Mangaroska et al., 2018; Mor et al., 2015; Persico et al., 2015). Both create models of the learning process, LD represents the sequences of learning activities designed by teachers; while LA captures students behaviour while engaged in these activities (Griffiths, 2017). On the one hand, LA provides data and tools to test pedagogical assumptions in LD against actual student interactions. On the other hand, LD provides the necessary contextual overlay to better understand observed student behaviour and translate LA findings into actionable insights (Lockyer et al., 2011). Prior empirical works have shown the benefits of embedding LD in LA such as improving predictive accuracy of academic performance (Gašević et al., 2016), understanding the impact of LD on student engagement, satisfaction, and performance (Rienties & Toetenel, 2016b), and exploring the navigation sequence of learning activities (Ifenthaler et al., 2018).

Building on the intersection between LA and LD, the purpose of this thesis is to understand how teachers design activities for learning and how LD influences student behaviour in distance education. To set the stage for this thesis, the next section highlights the research motivations and gaps in the current literature. Section 1.2 presents the aims and the research questions of four empirical studies as well as their contributions. Finally, Section 1.3 outlines the structure of the remaining chapters of this thesis.

1.1 Problem Definition

Designing for learning is both an art and a science (Maina et al., 2015). There are explicitly structured components in LD which can often be found in a course syllabus. These include the number of credits, level of study, subject topics, learning materials, and course schedule. However, LD is also a creative process that leaves room for variety in how each teacher designs and scaffolds sequences of learning activities for their students to achieve the learning goals (Rienties et al., 2015; Toetenel et al., 2016b). For example, some teachers might prefer lectures and readings while others emphasise group work and interactive activities. Some teachers prefer a summative assessment (i.e., exams) at the end of a course while others continuously assess their students throughout the learning process. Each designing decision will influence how students engage with the course, as well as their academic performance (Rienties & Toetenel, 2016b).

A large number of LD tools and frameworks has been developed over the years to capture and describe sequences of learning activities. Early examples are Educational Language Modelling (EML) (Koper et al., 2004), and the Learning Activity Management System (LAMS) (Dalziel, 2003), while more recent ones include Learning Design Studio (Law et al., 2017), Learning Designer (Laurillard et al., 2018), and the Integrated Learning Design Environment (ILDE) (Hernández-Leo et al., 2018). Previous work reported that LD tools were positively perceived by teachers in facilitating new teaching ideas (Laurillard et al., 2018; Toetenel et al., 2016a), supporting a collaborative design process among practitioners (Hernández-Leo et al., 2018; Hernández-Leo et al., 2014; Hernández-Leo et al., 2011), and making the LD process more systematic (Dalziel, 2003; Koper et al., 2004). While prior research has provided important evaluations of LD tools from a user-experience perspective, only a few studies have explored how teacher design courses on a large scale in practice (Rienties et al., 2015; Toetenel et al., 2016b).

For example, Toetenel et al. (2016b) analysed 157 LD visualisations at the Open University (OU) and found that the majority of modules used assimilative activities (i.e., readings, watching, listening) and assessment (i.e., assignments, exams) activities. On average, assimilative and assessment activities accounted for 39.27% and 21.50% of the total workload respectively. Rienties et al. (2015) identified four patterns of LD amongst 87 modules, which they labelled constructivist, assessment-driven, balanced-variety, and social-constructivist. While these studies provided important insights into our understanding of LD, they did not explore how LD changes throughout the length of a course. For example, teachers use a wide range of learning activities varying from week to week or day to day throughout a course. The order and sequence of how learning activities are structured will potentially influence the effectiveness of the learning process. Therefore, **this thesis will address the gap in our understanding of how teachers design for learning in distance education and the temporal aspects of learning design.**

Although the documentation and visualisation of LD can make teacher’s pedagogical decisions of teachers more explicit, many factors behind the scene may not be visible to LD tools. These include pedagogical beliefs, personal experience, composition of the student body, and ‘politics’ within institutions (Bennett et al., 2015; Bennett, Agostinho, et al., 2017; Bennett, Dawson, et al., 2017; Bennett et al., 2011). Extensive research in the field has shown that LD is a multifaceted process which involved multiple stakeholders and different factors interacting in the process of designing and implementing teaching and learning activities (Bennett et al., 2015; Bennett, Agostinho, et al., 2017; Bennett, Dawson, et al., 2017; Conole, 2009; Lockyer et al., 2008). For instance, Bennett et al. (2015) conducted 30 interviews across 16 Australian universities to explore key influences that shape university teachers' design decisions. The authors identified student-related factors (e.g., cohort profile, learning objectives, feedback from past sessions), teachers-related factors (e.g., prior experience, pedagogical beliefs, self-belief), and context-related factors (e.g., colleges, institutional requirements, resources) that influenced how teachers engaged in the design process (Bennett et al., 2015). It is important to understand both *what* has been designed and *why* as well as *how* teachers design. Therefore, **this thesis will explore the underlying factors that influence teachers' LD processes**.

While LD decisions are largely driven by teacher experience and the learning environment, it is also important to consider student characteristics, behaviours, and performance in order to understand the effectiveness of LD (Mor et al., 2015; Persico et al., 2015). Research in LA offers new opportunities to unpack the process of how students engage with learning activities designed by teachers. At the same time, pedagogical insights gathered from LD tools can provide researchers with a narrative that goes beyond the numbers. This helps translate LA findings into meaningful feedback to teachers. While the connection between LA and LD has been extensively discussed in the literature (Bakharia et al., 2016; Lockyer et al., 2013; Mangaroska et al., 2018; Mor et al., 2015; Persico et al., 2015), there are limited empirical studies that have explored this topic (Gašević et al., 2016; Ifenthaler et al., 2018; Rienties & Toetenel, 2016a, 2016b; Rienties et al., 2015). For example, a large-scale study by Rienties and Toetenel (2016b) on 151 modules and 111,256 students indicated that LD significantly predicted student behaviour, satisfaction, and performance as well as increasing model performance by 13%. Similarly, Gašević et al. (2016) demonstrated how the effect of student behaviour on performance varied significantly across different instructional conditions. While these two seminal studies (Gašević et al., 2016; Rienties & Toetenel, 2016b) have provided important markers for LD and LA, they were conceptualised at a course level. As a result, the complex process of how learning behaviour changes over time has not been unpacked. Two recent special issues in the *Journal of Learning Analytics* have also pointed out the need for more temporal analytics research to move the field forwards (Chen et al., 2018; Knight, Friend Wise, et al., 2017a). For this reason, **this thesis will investigate how LD influences student engagement over time.**

1.2 Research Aims and Contributions

The overarching aim of this thesis is to understand how teachers design for learning and how LD influences student engagement in distance education. The present work sits at the intersection of LD and LA research, which acts as a bridge between data-driven research and educational theories. The empirical work in this thesis is composed of four studies, which are outlined below.

Study 1 started the empirical investigation by exploring how teachers design activities for learning through representations of learning activities in 37 undergraduate modules at a distance learning institution, the Open University UK, over 30 weeks. Using a combination of data visualisations and network analysis, Study 1 revealed common patterns and variations in LD over time across a large number of modules. By doing so, Study 1 addressed the following research questions:

Chapter 4 – Study 1. How teachers design for learning

RQ1.1 What are the temporal characteristics of learning design?

RQ1.2 How do different types of learning activity interact with each other?

While Study 1 has provided an overview of how teachers design activities for learning, Study 2 continues with an in-depth investigation into the underlying factors that influence the design process and the affordances as well as barriers that teachers face when adopting LD practices. Through a series of semi-structured interviews with 12 teachers, Study 2 provided a new understanding of the opportunities and challenges of implementing an LD tool at scale. This will help OU practitioners improve their approaches and provide useful lessons for other institutions that wish to implement their own LD tools. Furthermore, this study considers how teachers make use of the existing feedback on their module to support LD decisions. Findings from Study 2 will help explain the observed LD patterns in Study 1. Altogether, Study 2 addresses the following research questions:

Chapter 5 – Study 2. The underlying factors behind teachers' design decisions

RQ2.1 What are the driving factors behind teachers' design decisions?

RQ2.2 What are the barriers and affordances of learning design adoption at the OU?

RQ2.3 How do teachers make use of feedback on their module to support learning design?

After laying out the foundation for the understanding of LD through representations of learning activities and teacher perceptions, Study 3 examined the effect of LD on student behaviour, satisfaction, and performance. Through a large-scale analysis of 37 modules and 45,190 students over 30 weeks, findings from Study 3 helped validate existing assumptions in LD against actual student behaviour and triangulate findings from Study 1 and 2. Study 3 addressed the following questions:

Chapter 6 – Study 3. The impact of learning design on student engagement, satisfaction, and pass rate

RQ3.1 How do learning designs influence student behavioural engagement over time?

RQ3.2 How do learning designs influence student satisfaction and pass rate?

Study 4 took a further step to unpack the temporal aspect of student engagement to detect any potential mismatch between LD and student behaviour. The study also examines to what extent different patterns of engagement affect academic performance. Findings from Study 4 showcased how LA models informed by LD could provide teachers with actionable feedback to improve their teaching practices. Study 4 addressed the following question:

Chapter 7 – Study 4. The alignment between learning design and student behaviour, and its impact on academic performance

RQ4.1 How does students' timing of engagement align with learning design?

RQ4.2 How does students' timing of engagement relate to academic performance?

Overall, the four empirical studies described above bridged the gaps between LA and LD research by examining LD from three integrated dimensions: LD representations, teachers' perceptions, and students' behaviours (Figure 1). Employing a mixed-method design, this investigation used a combination of data visualisation, network analysis, qualitative interviews and multilevel modelling to help triangulate findings from the four studies. As a result, this thesis offers novel contributions to the understanding of both the design process and learning process in distance education.

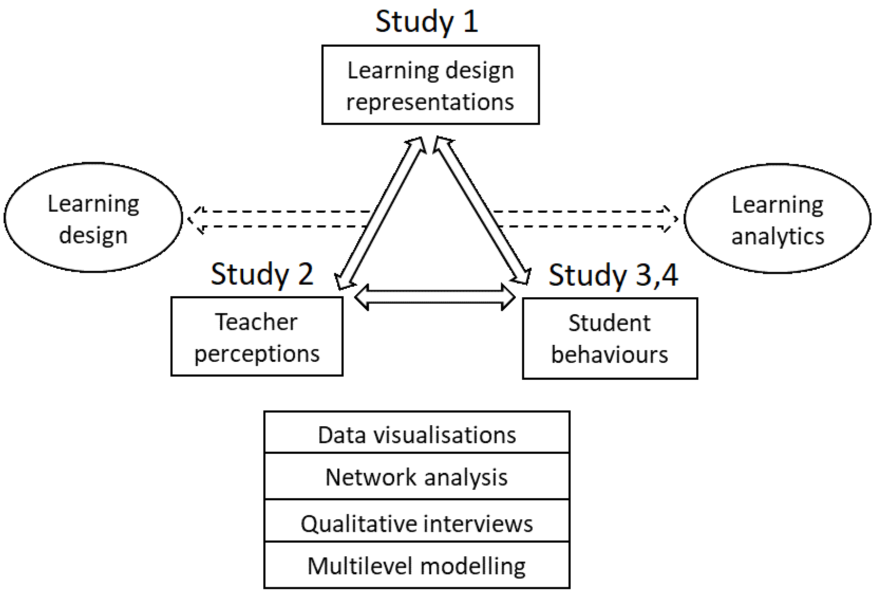

Figure 1. Key concepts and methods used in this thesis

1.3 Thesis Structure

The overall structure of the remaining chapters in this thesis are as follows:

Chapter 2: Literature Review

Chapter 2 presents an in-depth review of current research on the topics of LD and LA. The chapter highlights the current gaps in the literature, providing a rationale for the research questions addressed by this research.

Chapter 3: Methodology

Chapter 3 discusses the overarching methodologies and justifications for the pragmatic and mixed methods approach. It also describes the strengths and weaknesses of each methodological choice used to answer the research questions. The specific methods used for the four research studies are outlined in their corresponding chapters (Chapters 4 through 7).

Chapter 4: Study 1 Methods and Results

In Chapter 4, RQ1.1 and RQ1.2 are used to explore common temporal patterns and variations in LD. This chapter outlines the specific methods used to address these research questions, including information about the study setting, instruments, and data analysis. A brief discussion of the research findings is included, as well as the limitations of the study and implications for future work in the thesis.

Chapter 5: Study 2 Methods and Results

Study 2 triangulates the findings from Study 1 through in-depth qualitative interviews (RQ2.1, RQ2.2, and RQ2.3). Chapter 5 outlines the specific research methods used to address these research questions including research context, participants, and analysis procedures. Finally, a short discussion is provided, including the study's limitations and implications for the remaining studies.

Chapter 6: Study 3 Methods and Results

Study 3 was a large-scale study to explore the impact of LD on student engagement (RQ3.1), satisfaction, and retention (RQ3.2). The chapter describes the methods used to answer these research questions, including the setting, participants and analysis procedures. The findings are discussed in the chapter, along with the study's limitations and implications for further work.

Chapter 7: Study 4 Methods and Results

Building on findings from Study 3, Study 4 carried out a fine-grained analysis of the temporal characteristics of student engagement and its relations to LD (RQ4.1) and academic performance (RQ4.2). The chapter describes the methods used to answer these research questions, including the setting, participants and analysis procedures. The wider implications and limitations of these findings are covered in a brief discussion.

Chapter 8: General Conclusions and Discussion

The final chapter synthesises the findings of the four studies, by providing final conclusions and outlining novel theoretical and methodological contributions to the field of LD and LA. In addition, implications and suggestions for practices are provided. The chapter concludes the thesis by discussing overarching limitations of this work and directions for future research.

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Chapter 2 - Literature Review

2.1 Introduction

Drawing upon two strands of literature in learning analytics (LA) and learning design (LD), this chapter seeks to explore the synergy between the two fields and identify the research gaps to be addressed in this thesis. Chapter 2 is divided into two parts: LD (Section 2.2) and LA (Section 2.3). Section 2.2 starts by discussing the existing progress in developing LD representations, followed by a synthesis of four LD taxonomies that are being used to classify learning activities, and analyses the current research gaps in LD. Section 2.3 first reviews the current progressing LA, then discusses its challenges and highlights the synergy between LA and LD. Finally, Section 2.4 summarises the research questions and concludes the chapter.

2.2 Learning Design

Learning design is a widely used term by researchers and practitioners in education. However, LD as a field refers to a body of literature emerging in the early 2000s as a result of the increasing presence of constructivist paradigm in education coupled with the emergence of online and technology-enhanced learning (Dalziel et al., 2016; Dobozy et al., 2018; Lockyer et al., 2008; Maina et al., 2015). A common metaphor of an LD is a music notation which contains enough information to convey musical (teaching) ideas from one to another over time and space (Dalziel et al., 2016). While the field of LD has progressed substantially for the last 20 years, there has been no conceptual unity in the definition of LD which reflects the complex nature of the field (Dalziel et al., 2016; Dobozy et al., 2018). Table 1 compiled a list of definitions as an overview of the evolution in thinking about LD over time.

Table 1. Overview of learning design definitions

Author(s)	**Definitions**
Agostinho (2006, p. 3)	A representation of teaching and learning practice documented in some notational form so that it can serve as a model or template adaptable by a teacher to suit his/her context
Koper's (2006, p. 13)	The description of the teaching-learning process that takes place in a unit of learning (e.g., a course, a lesson or any other designed learning event).
Mor and Craft (2012, p.86)	The creative and deliberate act of devising new practices, plans of activity, resources and tools aimed at achieving particular educational aims in a given context

Dobozy (2013, p.68)	A way of making explicit epistemological and technological integration attempts by the designer of a particular learning sequence or series of learning sequences
Conole (2013, p. 121)	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
Dalziel (2016, p.4)	The new field of Learning Design seeks to develop a descriptive framework for teaching and learning activities ("educational notation") and to explore how this framework can assist educators to share and adopt great teaching ideas.

As can be seen from Table 1, there are three core features of LD that are present through all different definitions: developing tools to describe and represent LD, providing guidance for teachers during the LD process, and sharing LD practices between practitioners. While there are many different definitions of LD, this thesis operates on the definition laid out by Dalziel (2016) in the "The Larnaca Declaration on Learning Design" in 2016 which gathered leading experts in the field. This definition was selected because it captures the three salient elements of LD research: representations, guidance, and sharing (Dalziel et al., 2016). The main premise is that by developing a descriptive framework to document sequences of learning activities, it will help teachers reflect on their existing LDs, guide the design process, and share best practices with each other (Conole, 2012; Dalziel, 2015; Dalziel et al., 2016; Lockyer et al., 2008).

Although the body of LD literature emerged in the early 2000s, the science of instructional design has been around for over six decades (Dick, 1987; Reiser, 2001). The origin of instructional design (ID) can be traced back to World War II where a large number of psychologists were called to conduct research and develop educational materials for the US military services. Research in ID is driven by behaviourism and cognitivism paradigm (i.e., Skinner, Gagne) while LD is influenced by a constructivism paradigm (i.e., Piaget, Vygotsky). A key distinction between ID and LD is that the former focuses on making the design process more systematic, while the latter aims at making the existing design more explicit, sharable, and reusable (Persico et al., 2015). ID focuses on what teachers do while LD put more emphasis on what students do. Research output in ID are systematic models such as ADDIE (analyze, design, develop, implement, and evaluate), Dick and Carey systems approach model, and ASSURE (analyze students, state objectives, select media and materials, utilise materials, require student participation, and evaluation/review). Research output in LD includes tools and specifications such as LAMS, EML-ID, and OULDI which are described below. The terms learning design and instructional design are being used interchangeably by practitioners. However, because of its historical origin, the term “instructional design” is more popular in the United States and Canada while the term “learning design” is frequently used in Europe and Australia.

To develop a descriptive framework of learning activities, researchers need two components: a suitable method to represent LDs and an appropriate language to describe LDs. These two components are described in the sections below.

2.2.2 Learning design representation

At the core of LD is a representation, which can be understood as an approach to document and describe teaching and learning activities (Dalziel et al., 2016). A common metaphor of LD representation is a music notation which contains enough information to convey musical (teaching) ideas from one to another over time and space. By developing an educational notation to describe existing LDs, educators can reflect on their practices, while re-use and adapt good LDs from others.

LD representations can take the format of visual representations or textual representations. Textual representations can be expressed in formal/artificial languages to be processed by computers or in natural languages following a narrative. Visual representations often take the form of graphs or diagrams, to represent the main entities within a design and their mutual relationships (Persico et al., 2015). LD representations can take place at different levels of granularity such as program, module, session, and learning activities (Dalziel et al., 2016). In the last 15 years, there has been a large number of research projects focusing on developing tools and approaches to make LD explicit through visual and textual representations (Table 2) (AUTCLearningDesign, 2002; Conole, 2012; Dalziel, 2003; Hernández-Leo et al., 2014; Koper et al., 2004; Laurillard et al., 2018; Law et al., 2017; McAndrew et al., 2006).

Table 2. Learning Design representation tools

Project	**Authors**	**Type**	**Purpose**
EML (Educational Modelling Language) IMS-LD	Koper et al. (2004)	XML languages	Representation Sharing Reusability
LAMS (Learning Activity Management System)	Dalziel (2003)	Diagram	Representation Monitoring Reusability
ILDE (Integrated Learning Design Environment)	Hernández-Leo et al. (2018)	Diagram	Representation Sharing
Learning Designer	Laurillard et al. (2018)	Diagram	Representation Sharing
LD studio	Law et al. (2017)	Diagram	Representation Sharing
OULDI (OU Learning Design Initiative)	Cross et al. (2012)	Diagram	Representation Sharing
AUTC (Australian Universities Teaching Council)	AUTCLearningDesign (2002)	Narrative	Representation Sharing

An example of an LD representation using artificial languages is the work of Koper (2001); Koper et al. (2004); Koper et al. (2003), first on Educational Modelling Language (EML) and subsequently Instructional Management Standards Learning Design Specification (IMS-LD). In this research project, the authors developed a semantic, formal and machine-interpretable specification of the LD, which is defined as the description of the teaching-learning process that takes place in the unit of learning. The core concept of IMS-LD consists of the following components: A person gets a role (e.g., student or teacher). The person works towards certain outcomes by performing learning or teaching activities within an environment. The LD method is designed to provide the coordination of roles, activities and associated environments that allows students to meet learning objectives. It was then visualised using a UML diagram and then codified into an XML file, which can be read by other digital LD engines.

The repositories of exemplars LD by the Australian University Teaching Committee (AUTC) project is an example of a narrative based LD representations (AUTCLearningDesign, 2002). The project aimed to produce generic/reusable LD resources to assist academics to create high quality, flexible learning experiences for students. These include a wide variety of guidelines, ICT tools, and a collection of exemplar LDs. Educators can browse from a list of over 30 exemplar LDs categorized by five foci: collaborative, concept/procedure development, problem-based learning, project/case study, and role-play. Users can also filter the exemplars by other criteria such as discipline, ICTs used, or author. Once the users select an exemplar, they can view a snapshot of the LD with a written summary. The user can also view the respective LD using a visual format for illustrating the flow of activities over time. As of 2019, the website seems to no longer be updated[1].

The Learning Activity Management System (LAMS) is one of the foundation projects in LD since 2005 and still going on as of 2019[2] (Dalziel, 2015; Dalziel et al., 2016). LAMS is an open-source system for designing, managing and delivering online collaborative learning activities. It provides teachers with a visual authoring environment for creating sequences of learning activities. Teachers can create a learning sequence by selecting components of learning activities and link them together using drag and drop functions. The learning sequence can be integrated into LMS systems such as Moodle. However, the integration into LMS systems require technical configurations from an institutional level and would certainly increase teachers' workload.

[1] http://www.learningdesigns.uow.edu.au/
[2] https://www.lamsinternational.com/

One of the rationales for making LD explicit is to facilitate knowledge exchange in the LD process. For example, the Integrated Learning Design Environment (ILDE), previously LdShake, is a community platform to enable collaboration between practitioners for sharing and co-editing both conceptualizations and fully-fledged authored LDs (Hernández-Leo et al., 2018; Hernández-Leo et al., 2014; Hernández-Leo et al., 2011). The ILDE offers practitioners access to multiple conceptualizations tools to sketch preliminary ideas for their LDs (e.g Persona card, Course Features, Course Map, CompendiumLD). Users then can use authoring tools to produce full-fledged definitions of LDs provided by the integrated Web Collage (Villasclaras-Fernández et al., 2013) and OpenGLM (Derntl et al., 2011) editors. The LDs can then be deployed to VLEs. Users can choose to share the conceptualization, authoring and deployed process with other users in the system. They can choose to browse other LDs based on tags, adding comments and discussion, and duplicate an LD for reuse. The authors reported overall positive evaluations from 107 workshops attendee and extensive usage of the ILDE tools based on user trace data on its system.

As can be seen from Table 2, most LD representation tools used diagrams or flowcharts to capture sequences of learning activities. Visual representations of LD allows educators to have a quick overview of their course and the proportion of each learning activity type that make up the whole course (Laurillard et al., 2018; Law et al., 2017; Toetenel et al., 2016a). In addition, the sequential order of learning activities can be represented using flowcharts which allows educators to reflect on the coherence and logic of their LD (Dalziel, 2003; Hernández-Leo et al., 2018; Law et al., 2017). Textual representations of LD such as the description of a lesson plan give richer information and capture the nuances that might not be present in visual representations (AUTCLearningDesign, 2002). However, textual representations are time-consuming, and not comparable across different courses. While most of the LD tools focus on developing representations, only two of them (EML and LAMS) allow users to integrate their LD representations into LMS systems.

Although the field of LD aims at developing a common descriptive framework to describe teaching and learning activities, there has been no consensus on a common educational notation to date (Dalziel et al., 2016; Dobozy et al., 2018; Maina et al., 2015). This poses a great challenge as the field progresses because new LD projects arising without a common language will create silos of knowledge. As a result, it creates a major barrier in sharing and reusing existing LDs for practitioners as well as replicating and reproducing scientific knowledges for researchers in the field of LD. The next section will dive in-depth into the four major taxonomies used in LD research and compare and contrast their similarities and differences as well as strengths and weaknesses: Bloom's taxonomy and the revised Bloom's taxonomy (Anderson et al., 2001; Bloom, 1956), the Conversational Framework (Laurillard, 2002), the Learning activity taxonomy (Conole, 2007; Conole, 2012), and the Learning Design pattern language (Law et al., 2017).

2.2.2 Taxonomies of learning activity

Taxonomy refers to the practice and science of classification of things or concepts, including the principles that underlie such classification (Linnaeus, 1758). For example, in biology, animals are classified based on common ancestors or genetic traits. In economics, taxonomies are used to classify economic activities, companies and sectors, such as Standard Industrial Classification (SIC). Taxonomies are fundamental in advancing scientific progress as they represent a common language and thinking system. Without a reliable taxonomy, scientific progress will be inefficient as there are duplications and confusions across scientific findings. Although the concept of taxonomy started in Biology with Carl Linnaeus (Linnaeus, 1758), it has moved into other areas such as education with the Bloom's taxonomy and the Bloom's revised taxonomy (Anderson et al., 2001; Bloom, 1956). Educational taxonomy plays a vital role in guiding researchers to systematically conceptualizing their research to develop a new theoretical framework and learning theories.

Although there are many taxonomies in education research, I will focus on reviewing four taxonomies that have been extensively used and embedded in the field of LD: 1) Bloom's taxonomy by Anderson et al. (2001); Bloom (1956) which is foundational in the development of ID and LD; 2) the Conversational Framework by Laurillard (2002) which underpinned the Learning Designer tool at UCL[3]; 3) the learning activity taxonomy by Conole (2007); Conole (2012) which underpinned the LD research[4] at the OU, 4) and the LD pattern language by Law et al. (2017) which underpinned the Learning Design Studio[5] at Hong Kong University.

2.2.2.1 Bloom's taxonomy

In 1956, Benjamin Bloom and colleagues published a framework to categorize educational goals entitled "Taxonomy of Educational Objectives", also famously known as Bloom's taxonomy (Bloom, 1956). This framework consists of six levels within the cognitive domain: Knowledge, Comprehension, Application, Analysis, Synthesis, and Evaluation (Table 3). In 2001, another team of scholars led by Lorin Anderson, a former student of Bloom's, and David Krathwohl, one of Bloom's colleagues as he devised his classic cognitive taxonomy, published a revised version of the Bloom's taxonomy (Anderson et al., 2001). The revised Bloom's taxonomy changed the names of the six categories from nouns to verbs: Remember, Understand, Apply, Analyse, Evaluate, and Create (Table 3). These action words reflect a more active form of thinking and working with knowledge by students.

[3] https://www.ucl.ac.uk/learning-designer/
[4] https://iet.open.ac.uk/themes/learning-analytics-and-learning-design
[5] http://lds.cite.hku.hk/

Table 3. Bloom's taxonomies

Bloom's taxonomy 1956	Revised Bloom's taxonomy 2001	Meaning
Knowledge	Remember	Recognizing or recalling knowledge from memory. Remembering is when memory is used to produce or retrieve definitions, facts, or lists, or to recite previously learned information.
Comprehension	Understand	Constructing meaning from different types of functions be they have written or graphic messages or activities like interpreting, exemplifying, classifying, summarizing, inferring, comparing.
Application	Apply	Carrying out or using a procedure through executing or implementing. Applying relates to or refers to situations where learned material is used through products like models, presentations, interviews or simulations.
Analysis	Analyse	Breaking materials or concepts into parts, determining how the parts relate to one another or how they interrelate, or how the parts relate to an overall structure or purpose. Mental actions included in this function are differentiating, organizing, and attributing, as well as being able to distinguish between the components or parts. When one is analysing, he/she can illustrate this mental function by creating spreadsheets, surveys, charts, or diagrams, or graphic representations.
Evaluation	Evaluate	Making judgments based on criteria and standards through checking and critiquing. Critiques, recommendations, and reports are some of the products that can be created to demonstrate the processes of evaluation. In the newer taxonomy, evaluating comes before creating as it is often a necessary part of the precursory behaviour before one creates something.
Synthesis	Create	Putting elements together to form a coherent or functional whole; reorganizing elements into a new pattern or structure through generating, planning, or producing. Creating requires users to put parts together in a new way or synthesize parts into something new and different creating a new form or product. This process is the most difficult mental function in the new taxonomy.

Furthermore, the revised Bloom's taxonomy also described different types of knowledge – factual, conceptual, procedural, and metacognitive and their intersections with the six categories in the cognitive process (Table 4).

Table 4. Bloom's knowledge dimensions

Knowledge dimension	Definition
Factual Knowledge	The basic elements students must know to be acquainted with a discipline or solve problems.
Conceptual Knowledge	The interrelationships among the basic elements within a larger structure that enable them to function together.
Procedural Knowledge	How to do something, methods of inquiry, and criteria for using skills, algorithms, techniques, and methods.
Metacognitive Knowledge	Knowledge of cognition in general as well as awareness and knowledge of one's own cognition

Bloom's taxonomy plays an instrumental role in designing curriculum and assessment in higher education. A recent systematic review of the use of the Bloom's taxonomy in computer science education based on 41 publications suggested that the taxonomy was most frequently used for designing assessments (Masapanta-Carri et al., 2018). This includes developing questions or problems aimed at given cognitive levels, classifying questions or problems previously developed into cognitive levels, and classifying students' performance into cognitive levels. Other applications of Bloom's taxonomy in computer science education includes scheduling instruction, specifying learning goals, developing new taxonomies, and developing educational software. The taxonomy has become a standard for describing learning outcomes of 21st-century university teaching in many administrative documents (i.e., the Bologna process documents) (Murtonen et al., 2017).

Despite its popularity, the Bloom's taxonomy has been reported as difficult to use due to various reasons (Griffiths et al., 2005; Masapanta-Carri et al., 2018; Murtonen et al., 2017). Firstly, as a high-level classification system, the taxonomy does not account for the disciplinary differences in course design (Masapanta-Carri et al., 2018). Secondly, there remain overlaps between different categories which lead to inconsistent in categorization. For example, writing a report entails understanding, analysing, applying, synthesising and creating. The issue of interpretation is also present in all other taxonomies. Thirdly, the interpretation of each level of the taxonomy, as well as the cognitive effort, are different between experienced and novice teachers. For example, taking notes could be a part of remembering factual knowledge but also a way to synthesise different conceptual knowledge. Finally, due to the epistemological origin of the Bloom's taxonomy (i.e., behaviourism), it does not cover social constructivism learning activities such as discussion, or collaboration (Masapanta-Carri et al., 2018; Murtonen et al., 2017).

2.2.2.2 Conversational Framework

The Conversational Framework of Laurillard (2002) aims to represent the teaching and learning process as an iterative dialogue between teachers, students, and the learning environment (Laurillard, 2002). It is inspired by Vygotsky, Piaget, and Dewey's constructivism learning paradigm, and Gordon Pask's Conversation Theory which proposed that knowledge is constructed through conversations between two or more cognitive systems such as teachers and students or students and students (Pask, 1976). The Conversational Framework encompasses four different communication cycles: teacher communication cycle, teacher modelling cycle, peer communication cycle, and peer modelling cycle (Laurillard, 2002, 2012). For example, a lecture is an example of the teacher communication cycle, in which teachers communicate certain concepts to students and students can ask teachers questions to clarify their understanding. Peer communication cycle occurs, for example, when two students having a discussion about a topic. These 'communication cycles' emphasise the exchange of conceptual knowledge, whilst the 'modelling cycles' focus more on the exchange of practices. For example, the teacher modelling cycle occurs when teachers give written feedback on students' essay. An example of peer modelling cycle is a group presentation.

The Conversational Framework underpinned the Learning Designer, a web-based tool[6] to support teachers in designing practices based on the idea of "teaching as a design science" (Laurillard, 2012). The Learning Designer tool was developed to help teachers plan a sequence of learning and teaching activities using six learning activity types including acquisition, inquiry, practise, production, discussion, and collaboration (Table 5) (Laurillard, 2012; Laurillard et al., 2018).

Table 5. Laurillard's Conversational Framework

Pedagogy	**Activity type**	**Examples**
Individual learning	Acquisition	Listening to a lecture or podcast, reading from books or websites, and watching demos or videos.
	Inquiry	Explore, compare and critique the texts, documents and resources that reflect the concepts and ideas being taught.
	Practice	Practising exercises; doing practice-based projects, labs, field trips, face-to-face role-play activities.
	Production	Producing articulations using statements, essays, reports, accounts, designs, performances, artefacts, animations, models, videos

[6] http://beta.learningdesigner.org/index.php

Social learning	Discussion	Tutorials, seminars, email discussions, discussion groups, online discussion forums, class discussions
	Collaboration	Small group project, using online forums, wikis, chat room

In a recent evaluation of the Learning Designer tool based on 55 post-course surveys, Laurillard et al. (2018) showed that teachers could see the benefit of the tool and intend to use it for their teaching practices. Further qualitative data indicated that teachers find the taxonomy useful for critical reflection on elements of existing LDs and to foster better pedagogy. Trace data from the tool also suggested an increasing trend in the number of visitors and pageviews over time.

A key distinction between the Conversational Framework and Bloom's taxonomy is the social element of learning through discussion and collaboration activities. This reflects the evolution in teaching and learning paradigm as collaborative activities are increasingly embedded in LD. However, one caveat of the Conversational Framework's activity taxonomy was the lack of a separate category for assessment activities. Instead, assessment activities fell under the production category as students produce learning artefacts (e.g., essays, reports, presentations) based on what they have learnt. Although students always produce learning artefacts as a part of assessment activities, there is a difference between their purposes (i.e., production activities put a stronger emphasis on helping learners reflect on existing knowledge by producing essays, reports, presentation while assessment activities focus more on evaluating knowledge comprehension) and the motivation of students in each type of activities (i.e., non-graded vs graded activities). Furthermore, because assessment design is a major part of LD with many variations (e.g., formative, summative, self, peer) (Earl et al., 2006; Panadero et al., 2017; Pereira et al., 2016; Torrance, 2007), it is imperative for a taxonomy to capture the essence and complexity of assessment activities.

2.2.2.3 Learning activity profile

The Learning Activity profile was developed as a part of a strategic institutional LD initiative at the Open University (i.e., OULDI) funded by JISC in 2008 (Cross et al., 2012). The taxonomy was designed by Conole (2007) and colleagues to help teachers (and students) map different types of learning activity across a course or sequence of learning events. The underlying principles of the OULD taxonomy are the concept of mediating artefacts (Conole, 2012), which were grounded in a sociocultural perspective (Vygotsky, 1980) and activity theory (Engeström et al., 1999). The central idea of a sociocultural perspective is the notion that the process of cognitive development is contextually and socially bound. Thus, this recognizes that learning activities depend on the context within which they take place. The use of activity theory highlights the relationship between different components embedded in the design process and its context. Learning activities mediate between the users and the end goals. If these activities can be abstracted and represented in a meaningful and understandable way, there is a greater chance of them being picked up, used and adapted by others. There are six activity types: assimilative, finding and handling information, communication, productive, experiential, interactive/adaptive, and assessment (Table 6).

Table 6. Conole's Learning Activity Profile

Taxonomy	**Definition**	**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.

The Learning Activity profile is a fundamental component in LD research and practice at the OU. For example, Toetenel et al. (2016a, 2016b) compared the difference in 147 LDs before and after an LD workshop and concluded that the pedagogic decisions that educators made substantially changed. Courses that were designed after the introduction of LD workshop were more focused on the development of a range of skills and included fewer assimilative activities. Further comprehensive analysis of 157 LDs which were represented using the Learning Activity profile found that assimilative and assessment activities are the two predominant learning activity types accounting for 39.27% (SD=17.17%) and 21.50% (SD=14.58%) of the total workload.

Compared to Bloom's taxonomy and the Conversational Framework's learning activity taxonomy, the Learning Activity profile both captured the social learning aspect (i.e., communication) and evaluation activities (i.e., assessment). Both the Learning Activity profile and the Conversational Framework have similar categories, such as acquisition (assimilative), inquiry (finding and handling information), and production (productive). However, the activity profile differentiates between practising in a simulated environment (i.e., interactive) and in a real-world environment (i.e., experiential). On the other hand, the Conversational Framework differentiates between discussion and collaboration while the Learning Activity profile only has one communication category.

2.2.2.4 Learning Design pattern language

The LD pattern language was developed by Nancy Law and colleagues at the University of Hong Kong as a central part of the Learning Design Studio tool. Similar to the Conversational Framework and the activity profile, the LD pattern language was originated from a social constructivist learning paradigm, focusing on the role of students as active and self-directed, taking responsibility and agency for the learning process, with the teacher serving as a facilitator and motivator. However, the LD pattern language was underpinned by Alexander's Pattern Language (Alexander, 1977) which highlights different levels of granularity in design and the relationships between them. For this reason, the LD pattern language comprises of 12 fine-grained activity types, which are grouped into four pedagogical categories (Table 7).

Table 7. Law's Learning Design Pattern Language

Pedagogy	**Activity type**	**Definition**
Directed learning	Receiving & interpreting information	Work through prescribed content materials as instructed by the teacher
	Practice	Work through prescribed tasks to apply learnt content/skills
	Test/Assessment	Take part in assessment activities
Exploratory learning	Information exploration	Engage in information exploration through search, selection, and evaluation
	Exploration through conversation	Engage in the exploration of issues with others through conversations
	Tangible/immersive investigation	Engage in investigative exploration in physical or virtual settings
Productive learning	Construction: conceptual/visual artefacts	Work individually or together to construct a conceptual, visual artefact
	Construction: tangible/manipulable artefact	Work individually or together to construct a tangible artefact
	Presentation, performance, and illustration	Present, illustrate, or perform individually, or in group

Reflective learning	Reflection	Engage in reflecting on the learning process and experience and making their thoughts explicit
	Revision	Revise and resubmit a piece of work
	Self/peer assessment	Engage in peer or self-assessment (using self-generated or teacher-provided rubric)

The larger number of activity types allow users to capture and articulate their LD at a more fine-grained level of granularity. For example, assessment activities consist of reflection, revision, self/peer assessment, and traditional assessment. However, the more categories, the more likely that they will overlap between each other, making it difficult for classification purposes. For example, making a presentation could fall between “Construction: conceptual/visual artefacts” and “Presentation, performance, and illustration”. Because the LD pattern language and the LD Studio are in their infancy, there is little information on the efficacy of the tool and as well as the taxonomy. Based on the review of literature, Table 8 synthesises the four taxonomies and the associations between their activity types.

Table 8 was organised according to the similarity in categorical definitions between the four learning taxonomies. For example, ‘remember’ and ‘understand’ in the Bloom’s taxonomy are synonymous with ‘acquisition’ in the Conversational Framework, ‘assimilative’ in the Learning Activity Profile, and ‘receiving and interpreting information’ in the LD pattern language. Examples of such activities include reading textbooks, watching videos, or listening to podcast. Another example of shared meaning in categories was ‘evaluate’ in the Bloom’s taxonomy which was synonymous with ‘assessment’ in the Learning Activity Profile. The category of assessment was broken down further in the LD pattern language into ‘test/assessment’, ‘self/peer assessment’, ‘revision’, and ‘reflection’. Since there was no separate category for assessment in the Conversational Framework, the most relevant category is ‘production’ in which learners produce a wide range of artefacts that could be used for assessment, such as essays, reports, or presentation. It is worth mentioning that Table 8 refers my own interpretation of the four learning taxonomies, which might or might not concur with others’ interpretation. It is difficult to have a clear cut between these different categories. Nonetheless, when putting all the four learning taxonomies side-by-side, we can observe much overlaps and encompasses in many categories of learning activities

Table 8. A synthesis of four learning activity taxonomies

Revised Bloom's taxonomy	Laurillard's Conversational Framework	Conole's LD activity profile	Law's LD pattern language
Remember	Acquisition	Assimilative	Receiving & interpreting information
Understand			
Apply	Practice	Experiential	Practice
		Interactive	
Analyse	Inquiry	Finding & handling information	Information exploration
Evaluate	Production	Assessment	Test/Assessment
			Self/peer assessment
			Revision
			Reflection
Create	Production/Collaboration	Productive	Tangible/immersive investigation
			Construction: tangible artefact
			Construction: conceptual/visual artefacts
			Presentation, performance, and illustration
	Discussion	Communication	Exploration through conversation

Each of the four taxonomies above has its own strengths and weaknesses (Table 9). Although the older and more established Bloom's taxonomy has been widely used across the world, it does not capture the shift towards social aspects of learning in the 21st century with collaboration and discussion activities. The Conversational Framework consists of both individual and social learning dimensions. However, it does not consider the essence and complexity of assessment activities, which is a major part of any LD in higher education (Earl et al., 2006; Panadero et al., 2017; Torrance, 2007). The Learning Activity profile may combine the best of both worlds, taking into account both social learning and assessment activities. Furthermore, there is an emerging body of research that provide empirical evidence that this Learning Activity profile can explain and predict actual students' behaviour and engagement (Nguyen, Huptych, et al., 2018; Nguyen, Rienties, Toetenel, et al., 2017; Nguyen, Thorne, et al., 2018; Rienties & Toetenel, 2016b; Rienties et al., 2015). However, the Learning Activity profile does not allow for classifying learning activities at a more fine-grained level of granularity compared to the LD Pattern Language with 12 different activity categories. However, the larger number of categories also means that there is a lot of overlap between categories making the interpretation process more difficult for users.

Table 9. Strengths and weaknesses of four taxonomies (author's own interpretation)

Taxonomy	Authors	Applications	Strengths	Weaknesses
Bloom	Bloom; Anderson	Across higher education	High-level categorization Intersect with knowledge levels Widely use across the world	Interpretation depends on teachers' experience Does not account for social learning (discussion, collaboration)
Conversational Framework	Laurillard	UCL's Learning Designer tool	Accounts for both individual and social learning	Does not cover assessment
LD activity profile	Conole	OU's Learning Design Initiative	Accounts for both individual and social learning Large scale adoption within the OU UK and beyond. Rich empirical evidence showing a strong correlation with student behaviour	Does not differentiate between types of assessment
LD pattern language	Law	HKU's Learning Design Studio tool	More fine-grained categories Accounts for four different pedagogies	Overlapping categorization Lack of empirical evidence

The Learning Activity profile developed by Conole (2007) was chosen as the main theoretical framework for this thesis because it captures both the individual and social aspect of learning based on the seven types of learning activity. Furthermore, there have been a large amount of conceptual and empirical research using the Learning Activity profile to explore LD in online and distance education (Conole, 2007; Conole, 2009, 2012; Conole et al., 2004; Mittelmeier, Long, et al., 2018; Rienties et al., 2017; Rienties & Toetenel, 2016a, 2016b; Rienties et al., 2015; Rizvi et al., 2019; Toetenel et al., 2016a, 2016b; Whitelock et al., 2016). The Learning Activity profile has been a major part of LD practice at the OU, with applications to over 150 courses (Rienties & Toetenel, 2016a; Toetenel et al., 2016a) and has been adopted by other institutions such as the University of South

Africa (Mittelmeier, Long, et al., 2018). Since the study context of this thesis is at the OU, the Learning Activity profile is the most suitable framework given the availability of LD data as well as the wealth of existing research on this framework.

This session has critically reviewed four major learning activity taxonomies that have been widely used and embedded in LD tools. The next section will summarise the current research gaps in LD and argue how student learning behaviour can contribute to moving the field forward.

2.2.3 Challenges in LD research

Firstly, although LD representations are useful in describing design decisions at a meta-level, there are a lot of nuances that may not be captured through LD tools. LD is a complex process that is influenced by pedagogical, methodological, technological, and political factors (Bennett et al., 2015; Bennett, Agostinho, et al., 2017; Bennett et al., 2011; Dalziel et al., 2016). For instance, Bennett et al. (2015) conducted 30 interviews across 16 Australian universities to explore key influences that shape university teachers' design decisions. The authors identified student-related factors (e.g., cohort profile, learning objectives, feedback from past sessions), teacher-related factors (e.g., prior experience, pedagogical beliefs, self-belief), and context-related factors (e.g., colleges, institutional requirements, resources) that influenced how teachers engaged in the design process (Bennett et al., 2015). Their follow-up analysis focusing on the processes by which teachers design found that teachers approach LD as a top-down iterative process, beginning with a broad framework to which detail is added through cycles of elaboration. The design extends over the period before, while, and after a unit is taught, demonstrating the dynamic nature of design and highlighting the importance of reflection in teachers' design practice (Bennett, Agostinho, et al., 2017). The integration of technological innovation into design practices was perceived as desirable but is constrained by infrastructure, support, educator and student skills, and limited time (Bennett, Dawson, et al., 2017).

Clearly, the process of LD is context-dependent and situated within a larger ecological system that involves multiple factors. Understanding teacher design practices and their context is crucial to the development of LD tools and frameworks. Insights gathered from teachers would also support the interpretation of visual and textual representations of LD. However, there is a lack of empirical studies in LD research exploring teacher design practices. A recent systematic review of 20 empirical LD studies showed that 13 out of 20 papers were devoted to the evaluation of tools, 5 out of 20 papers investigated users' needs, and only 3 out of 20 papers analyzed teachers design practices (Dagnino et al., 2018). **Therefore, more research is needed to examine the driving factors behind teacher design decisions.**

Secondly, despite substantial progress in developing LD tools and frameworks as well as a large number of positive evaluation studies (Clifton, 2017; Hernández-Leo et al., 2018; Laurillard et al., 2018), LD has not been widely adopted as a standard practice by the education community at large (Dagnino et al., 2018). Up to now, many studies have reported on the positive affordances of LD practices (Clifton, 2017; Cross et al., 2012; Hernández-Leo et al., 2018; Laurillard et al., 2018) such as support for reflections on existing LD, support for reusing and adapting LDs, and facilitate cooperation amongst teachers. However, limited attention has been paid to the barriers that teachers face while they make use of LD tools and frameworks (Dagnino et al., 2018).

The benefits for teachers to engage in the LD practices might not worth the cost of learning and operating a complex new LD tool. For example, in a critical evaluation of IMS-LD, Goddard et al. (2015) identified five reasons why IMS-LD's progress has been so stunted despite a lot of attention it has received since the introduction in 2003. Based on 14 interviews of IMS-LD users, the authors suggested that:

- IMS-LD's purpose as an interoperability specification became sidelined
- IMS-LD tries to be all things to all people
- IMS-LD has not provided teachers and their institutions with compelling reasons to use it
- IMS-LD places too many demands on teachers, in their practice and in their relationships with institutions and students
- IMS-LD's origins in distance learning limit the potential for its widespread adoption

Although the study specifically focused on IMS-LD, its findings can potentially be generalised to other LD projects. Engaging in LD practice is a time-consuming process which put an extra burden on the workload of teachers without a clear benefit in return. Toetenel et al. (2016a) indicated that the process of 'mapping' a complete LD of a 60 credit module at the Open University UK takes 3-5 working days, with multiple iterations between learning designer and teachers to ensure the LD representation consistent with the actual LD. Goddard et al. (2015) also reported that it is time-consuming to document and create an LD specification given the complexity of IMS-LD. Clearly, previous studies have signalled some potential causes behind the slow uptake in LD tools and frameworks. In their systematic review, Dagnino et al. (2018) suggested that the lack of institutional support, lack of training, workload, conceptual complexity of method and tools, and motivations as some potential barriers to adoption of LD. The authors also made a point that all these factors were indirectly inferred from previous studies, which are often conducted in an experimental setting, rather than an explicit investigation into the barriers of adoption. Therefore, **there is a lack of studies exploring the perceived barriers to adoption of LD tools in an authentic environment**.

Thirdly, previous research in LD has collected a large amount of information about the design of a certain course through visual or textual representations. Each LD representation is a (simplified) pedagogical model that could potentially provide us with insights about the design decisions of teachers such as the type of learning activities, the amount of workload, or the sequential order when combining different activities together. However, only a few studies have utilised this information captured in LD tools to generate new insights into how teachers design their course. For example, Toetenel et al. (2016a) analyzed 157 LD representations at the Open University UK and found that most courses predominantly comprised of assimilative activities (e.g., reading, watching, listening) and assessment activities while there was little use of collaborative or interactive activity types. Rienties et al. (2015) performed a cluster analysis on 87 LD representations to identify four distinct patterns of LD namely social-constructivist, constructivist, assessment-driven, and balanced-variety. It is evident that LD representations can reveal many common patterns but also variations of LD across different modules and disciplines. Although previous findings have shed new light on our understanding of LD in distance education, they have not explicitly investigated the temporal characteristics of LD (i.e., how the design of learning activities varies throughout the length of a module). In comparison to existing approaches capturing sequences of learning activities, a temporal visualization of LD at a weekly level help user gain valuable insights of common trends and patterns in the design of their learning activities, which are more difficult to extract from a long sequence of learning activities. This is important because learning is a time-variant process. Teachers make changes in learning activities and workload throughout the course to best support different phases of learning (e.g., understand, apply, synthesize, evaluate). Research in LD provides a great opportunity to understand these temporal characteristics of LD through data collected about the sequences of learning activities. Therefore, **there is a need to better understand the temporal aspects of LD using the information generated from existing LD representations.**

The field of LD has a laudable aim of developing a descriptive framework – a common educational notation to capture teaching and learning activity and make LD explicit so that it can be shared and reused by other educators. However, there are many challenges in realizing this vision. The literature review has identified three main gaps in LD research:

- A lack of research exploring teacher design practices
- A lack of research investigating the affordances and barriers to adoption of LD tools in an authentic setting
- A lack of research examining the temporal characteristics of LD

To address the current gaps in LD research, this thesis proposed two studies. Firstly, Study 1 examines how teachers design for learning at the OU based on data generated from LD representations using the Learning Activity taxonomy. Study 1 aims to answer the following research questions:

- **RQ1.1** What are the temporal characteristics of LD?
- **RQ1.2** How do different types of learning activity interact with each other?

Secondly, Study 2 will explore the underlying factors behind teachers' design decisions as well as the affordances and barriers of adoption of LD tools. Not only will teachers' perceptions allow for a rich account of the complexities and nuances of LD but also help triangulate the findings from Study 1 which are based on LD representations. Therefore, Study 2 aims to answer the following research questions:

- **RQ2.1** What are the driving factors behind teachers' design decisions?
- **RQ2.2** What are the barriers and affordances of learning design adoption at the OU?
- **RQ2.3** How do teachers make use of feedback on their module to support learning design?

A potential direction to help the field of LD move forward is to align student feedback and behaviour with LD representations to refine and improve existing LD (Dalziel et al., 2016; Lockyer et al., 2013; Mor et al., 2015; Persico et al., 2015). The practise of collecting and analysing student responses to improve teaching quality has been around for decades (Richardson, 2005). Traditionally, formative and summative assessments have been used to indirectly evaluate LDs through how well students perform. In addition, course evaluations as self-reports are usually used to capture how satisfied students are with the course materials and teaching approaches (Li et al., 2017b). While these two formal sources of information (assessment and course evaluation) have been utilised by teachers to reflect on their teaching practices, they suffer from several limitations.

Firstly, summative assessment and course evaluations usually take place once the learning progress has finished, which prevent teachers from making in-time interventions (Wise et al., 2015). Secondly, assessment scores only assess what has been learnt, but not how students learnt and what can be improved in LDs. Thirdly, while self-report course evaluations provide a useful reflection of students on their learning experience, they are subject to sampling error, sampling bias, and response bias (Richardson, 2005). In particular, the response rate of course evaluation is relatively low, typically covering only a third of the whole population. Furthermore, survey respondents are usually biased toward particular groups of students (i.e., those who completed the course and perhaps performed well). Recent large-scale studies have shown that there was little to no correlation between student self-report satisfaction and their academic performance (Rienties & Toetenel, 2016a; Rienties et al., 2015). In other words, students might find a course entertaining but did not learn much and vice versa.

On the other hand, real-time feedback (verbally or behaviourally) of students while interacting with learning activities in class could be a rich source of information for teachers to reflect on (Dalziel et al., 2016). Nonetheless, its effectiveness might decrease as the class size increases or not applicable in other educational settings (e.g., online learning). For example, it is not possible to capture reactions of all 200 students in a lecture, or how they learn outside of class. A potential opportunity in online learning settings arises from the digital footprints left behind by student interactions in online learning platforms. By connecting LD representations to students' outcome, feedback, and behaviour, teachers can evaluate what works and what does not work in their LD. The next section will introduce LA and discuss how aligning LA and LD could address the challenges in both fields.

2.3 Learning Analytics

The field of Learning Analytics has experienced tremendous growth in the last 10 years with 6,370 publications indexed by Google scholar with the keyword "learning analytics" in 2018 (Figure 2). Starting from the first LAK conference in Banff, Canada in 2011, LA has attracted a lot of attention from practitioners, managers, and researchers in education by shedding light on a massive amount of potentially valuable data in education, as well as providing means to explicitly put traditional psychometric instruments and pedagogical theories into testing (Clow, 2013). LA brings together researchers from different backgrounds such as computer science, education, psychology, neuro-science, and behavioural science (Teasley, 2019). The interdisciplinary nature of the field has sparked new debates and novel applications of research methods across disciplines. By 2019, the LAK proceedings (30% acceptance rate) are ranked 7th in the top 20 most cited publication outlets in the subfield of Education Technology.

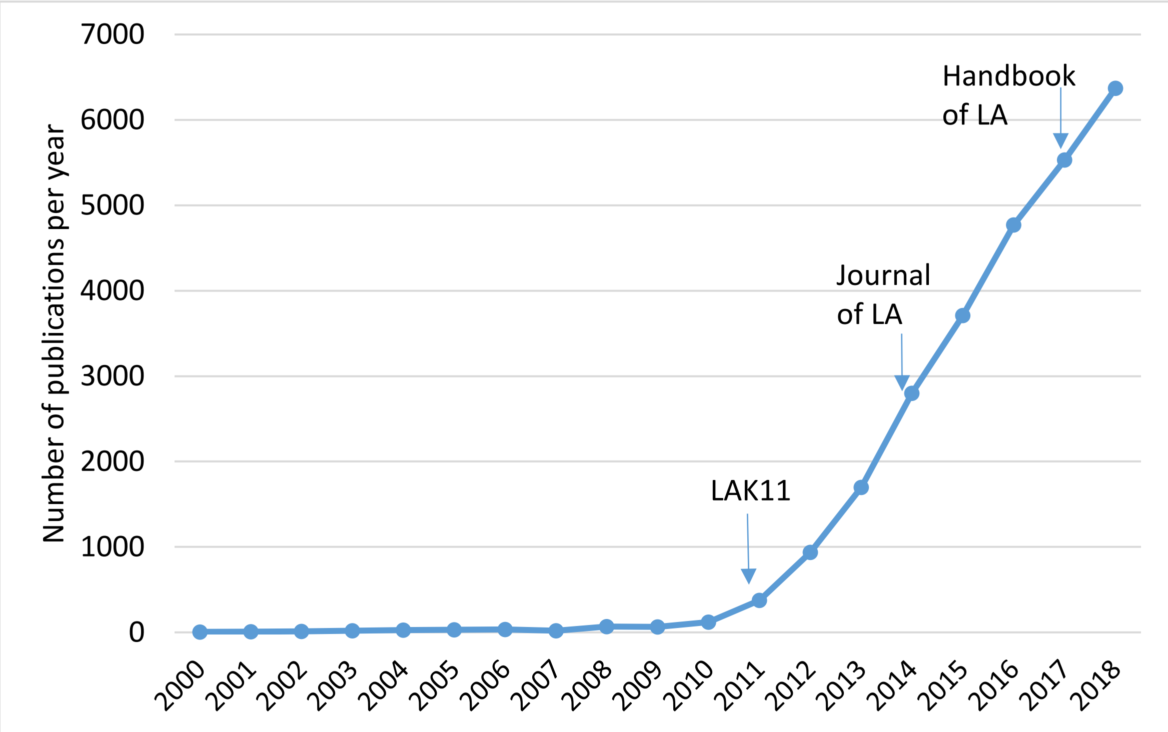

Figure 2. Publication trend in learning analytics on Google Scholar

The first and perhaps most successful application of LA in education is predicting academic performance or dropouts. An early work of Macfadyen et al. (2010) showed that LMS tracking data of 112 students in a fully online undergraduate biology course were able to explain more than 30% of the variation in final grade and correctly identified 81% of the students who failed the course. Romero et al. (2010) predicted whether a student passes or fail based on discussion forum interactions of 114 first-year students in computer science. The authors obtained an accuracy of 70%-80% in the middle of the course and 80%-90% towards the end of the course. The high predictive power of trace data and its scalability have paved the way for many systems to predict at-risk students in real-time such as Course Signal at Purdue University (Arnold et al., 2012), E-Coach at Michigan University (McKay et al., 2012), and OU Analyse at Open University UK (Kuzilek et al., 2015).

The second application of LA is the development of new measures, while cross-validating with self-report measures, for established educational construct such as self-regulated learning, academic engagement, and reflective thinking (D'Mello et al., 2017; Ullmann, 2019; Winne, 2017). Self-regulated learning is an ongoing process which consists of multiple stages such as surveying task conditions, setting goals and planning, engaging the task, and composing major adaptations for future tasks (Winne, 2017). Trace data, by its nature, allows researchers to capture factors and features of SRL throughout the learning process. For example, Winne (2006) developed the software nStudy, a browser plugin which allowed students to annotate, quote, and tag relevant information as they study. Trace data generated from nStudy provide a rich account of the SRL process as it opens the black box of cognitive strategies during the learning process. Van Laer et al. (2019) investigates whether providing cues for calibration affects students' self-regulated learning by examining changes in learning behaviour (computer logs) and academic performance. Kizilcec et al. (2017) investigated self-report SRL strategies of 4,831 students across six MOOCs and how these strategies manifest in online behaviour.

Methods used in LA are derived from the inter-disciplinary nature of the field. Most empirical research in LA is quantitative with some exceptions in policy and privacy research (Dawson et al., 2019; Viberg et al., 2018). In traditional education research, quantitative methods are mostly originated from inferential statistics based on the Frequentist paradigm with the aim to explain and generalise certain educational phenomena. In addition to the existing methods, LA research inherits other techniques from a vibrant field of computer science such as machine learning, natural language processing (NLP), social network analysis (SNA), sequential analysis, etc. The fusion of traditional statistics and data science techniques is a powerful driver of LA by allowing its researchers to analyse both structured (e.g., rows and columns) and unstructured data (e.g., texts, images) (Shum et al., 2016).

There are some differences in the kind of research questions asked in LA and 'traditional' education research. On one end of the spectrum is the prediction type of research questions, in which researchers are primarily concerned with optimising predictive accuracy (Brooks et al., 2017; Brooks et al., 2015; Musso et al., 2013). This is somewhat different from the goal of traditional education research, which is to gain an understanding of how people learn. However, this kind of research has direct applications for building new predictive systems to identify at-risk students, which is a priority in many higher education institutions. On the other end of the spectrum is the focus on the input-process-output model (Tempelaar et al., 2015). Traditional education research often follows an input-output model which correlates some self-report measures or interventions with academic performance. Because of the availability of data throughout the learning process, LA researchers can start unpacking the process of how students come to accomplish their academic outcomes.

2.3.1 Challenges in LA research

The unprecedented quantities of learning-related data available today provide researchers with exciting opportunities to study patterns and processes of how people learn. However, there is a danger in falling into the trap of thinking that with enough data, the numbers speak for themselves. Despite its impressive progress to date, the field of LA is still facing many challenges in refining its measurements, connecting to learning theories and pedagogy, and translating LA findings into actionable insights (Crawford, 2011; Gašević et al., 2015; Griffiths, 2013; Wise et al., 2015).

Firstly, larger datasets are not always better data (Crawford, 2011). From a statistical point of view, bigger datasets allow researchers to increase their sample size up to millions of students and the generalizability of their findings to a wider population of students. However, there is a well-known phenomenon in big data research called “garbage in garbage out”. For example, trace data from a course where the VLE is solely used for notes keeping purposes will not tell us much about how students learn (e.g., the click counts of downloading lecture slides). The number of clicks can also be a by-product of how the course interface was designed or the digital platform used (i.e., Moodle, Canvas) which has nothing to do with how students learn. Building a statistical model without an understanding of the data and their context will produce misleading findings. Another feature of big data is that not all data are equivalent (Crawford, 2011). For example, there is a difference between trace data of learning activities (e.g., student discussion in a forum) and trace data of administration/organisation tasks in a learning environment (e.g., teacher announcement in a discussion forum). Due to the central limit theorem, with a sufficient number of data points, something will always become statistically significant. However, a statistically significant variable does not always equate a large effect size. A variable with $p = 0.01$ in 2 million data points might only have an effect size Cohen’s on the order of 0.004, which indicates that the variable increases or decreases academic performance by 0.04%. In other words, statistical analysis in macro data might produce micro results.

Furthermore, the over-reliance on trace data may be problematic because of the difficulties in creating reliable metrics, as well as interpretation. Trace data are often used as proxies of academic engagement (Azevedo, 2015; Tempelaar et al., 2015). However, engagement is a multi-dimensional construct which consists of behavioural engagement, cognitive engagement, and emotional engagement (Sinatra et al., 2015). The inferences from trace data are usually limited to behavioural engagement only (Azevedo, 2015). Students can exhibit a high level of behavioural engagement (i.e., spend a lot of time on VLE) but they might not be cognitively engaged with the learning tasks (i.e., watching YouTube). Behavioural engagement patterns based on trace data are also difficult to interpret without instructional contexts. For example, a decrease in the level of engagement could be explained by either a) the student was falling behind or b) a study break in course design. Gašević et al. (2016) demonstrated that the relationship between trace data and academic performance was moderated by instructional conditions. Rienties and Toetenel (2016a) established a strong correlation between different types of learning activity and time spent on VLE. Therefore, the lack of instructional context in LA research raises concerns as to the validity of LA findings and interpretations.

Secondly, many LA studies are focused on algorithm optimisation instead of building a better understanding of how people learn. While developing new and reliable analytical methods is important, researchers should not forget the 'learning' element in LA (Gašević et al., 2015). Without a pedagogically informed approach to data, LA researchers may struggle with deciding which variables to attend to, how to generalise the results to other contexts, and how to translate their findings into actions (Kirschner, 2016). As a consequence, LA researchers might fall into the trap of only measuring what is available instead of what is valuable and important, or as Paul Kirschner elegantly put it in his LAK16's keynote "only searching for the keys where the light is". Wise et al. (2015) argued six important functions of theory in the analysis of large-scale data:

- Theory gives researcher guidance about which variables to include in a model
- Theory gives researcher guidance about what potential confounds, subgroups, or covariates in the data to account for
- Theory gives researcher guidance as to which results to attend to
- Theory gives researcher a framework for interpreting results
- Theory gives researcher guidance about how to make results actionable
- Theory helps researcher generalise results to other contexts and populations

Thirdly, many behavioural patterns can be identified from student activities, such as the number of clicks, discussion posts, or essays completed. However, these patterns alone are not sufficient to offer feedback that teachers can put into actions (Gašević et al., 2016; Rienties, Boroowa, Cross, Kubiak, et al., 2016; Tempelaar et al., 2017). For example, a recent large-scale study reviewing the use of predictive analytics tools with 240 teachers in 10 modules at the OU revealed that while teachers expressed interest in using predictive LA data in the future to better support students at risk, there has not been a clear benefit between groups of teachers having access to predictive LA data and groups of teachers that had no access (Herodotou et al., 2017). One potential explanation for this could be that the predictive analytics tool (i.e., OU Analyse) only provided information about the students' level of engagement on the VLE and their likelihood to pass a course. However, the analytics model has not been able to explain why students displayed certain behavioural patterns or which learning materials need to be amended. Both internal conditions (e.g., motivation, cognition, emotion) and external conditions (e.g., learning design, learning equipment) could affect student behaviour (Winne et al., 1998). Therefore, from the teacher's point of view, it is difficult to derive interventions based on predictive information without understanding the context (i.e., learning design) in which these behaviours took place. One way to address the above challenges, as suggested by Gašević et al. (2015) is to take into account the instructional context, which is discussed below.

2.3.2 Connecting learning analytics and learning design

Given the increasing need to make use of student data to provide feedback on teaching practices, and the importance of taking into account instructional context in large-scale data analysis, the two fields LD and LA begin to blend themselves together to reveal the complex interplay between teacher and student practices. The potential affordances and limitations in both fields have attracted an increasing interest to align LA with LD (Bakharia et al., 2016; Griffiths, 2017; Lockyer et al., 2011; Mangaroska et al., 2018; Mor et al., 2015; Persico et al., 2015). First, the analysis of trace data could equip educators with authentic and fine-grained proxies of how students engage in online learning activities. Second, by capturing and visualizing the design of learning activities, the LD approach could provide a pedagogical context to support interpreting and translating LA findings into interventions (Lockyer et al., 2013; Persico et al., 2015). For example, Lockyer et al. (2013) 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 students are carrying out their tasks. Persico et al. (2015) 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. They discussed three dimensions of LD that can be informed by LA: representations, tools, and approaches. Bakharia et al. (2016) proposed four types of analytics (temporal, tool specific, cohort, and comparative), and contingency and intervention support tools with the teacher playing a central role.

By making existing pedagogical models more explicit, LD can equip researchers with a narrative behind their numbers and convert trends of data into meaningful understandings and actionable insights. For example, Gašević et al. (2016) examined the extent to which instructional conditions influence the prediction of academic success in nine undergraduate courses offered in a blended learning model. By comparing the differences in the variability of grades explained by trace data metrics across different courses, their results suggested that it is imperative for LA to taking into account instructional conditions across disciplines and course to avoid overestimation or underestimation of the effect of LMS behaviour on academic success. In a large-scale study of 151 modules and their 111,256 students at the OU, Rienties and Toetenel (2016b) revealed relations between LD and VLE behaviour, along with student satisfaction, and retention. The findings showed that taking the context of LD into account could increase the predictive power of student behaviour by 10-20%.

In addition, Rodríguez-Triana et al. (2015) have illustrated the potential of orchestrating monitoring-aware design processes, and scripting-aware monitoring processes to support teachers to design CSCL activities. Rizvi et al. (2019) investigated the sequential engagement pattern of 2,086 students in a science MOOC course on FutureLearn and found that 'non-markers' type of students preferred assimilative activities such as watching videos or reading articles (87.46%) to communication (10.16%) and assessment activities (2.38%). Nguyen, Thorne, et al. (2018) studied the effect of study breaks on academic performance and student engagement of 123,916 undergraduate students in 205 modules from 2015–2017 at the Open University. The authors indicated a positive association between study breaks and the odds of passing a course (odd ratio = 1.28, $p<0.001$), while there was no statistically significant effect in relation to the number of assessment preparation and revision weeks.

Although there were numerous conceptual discussions in aligning LA with LD, the number of empirical studies on the subject has been rather limited (Gašević et al., 2016; Rienties & Toetenel, 2016b; Rienties et al., 2015). The study of Gašević et al. (2016) pointed out the difference in the effect of LMS trace data on performance between courses. However, the authors did not specifically examine aspects of the course design and how LD influences LMS learning behaviour. Two studies of Rienties and Toetenel (2016b); Rienties et al. (2015) took into account explicit LD representations and their association with student engagement and performance. However, two limitations of these studies were the collapse of all VLE activities under the average weekly time spent per course and the aggregated rather than a longitudinal perspective of LD. Since learning and teaching is a time-variant process, it is crucial to take into account fine-grained data from individual interactions in the VLE and investigate the effect of LD on student behaviour over time.

The importance of temporal analysis in LA research has been emphasised in the two recent special issues in the *Journal of Learning Analytics* (Chen et al., 2018; Knight, Friend Wise, et al., 2017a). Both LA and LD has the capability to collect fine-grained data about learning processes over a long period of time. The changes in learning behaviour over time largely depends on the sequences of learning activities designed by teachers. For example, courses with a continuous assessment strategy might have a more constant engagement pattern than courses with a mid-term and a final exam. The study workload assigned by teachers will influence the amount of time that students spend on studying.

Therefore, the next study in this thesis will examine how LDs influence student engagement, satisfaction, and pass rates:

- **RQ3.1** How do learning designs influence student behavioural engagement over time?
- **RQ3.2** How do learning designs influence student satisfaction and pass rate?

Finally, the last part of this thesis aims to explore to what extent student learning behaviours align with teachers' LD and how can we detect existing inconsistencies. When teachers design for learning, they often estimate the workload of each activity and the corresponding time period for each activity (e.g., take 3 hours to read chapter 2 in week 2). LD is often embedded in the course syllabus and acts as a guideline for students to self-regulate their learning process (Biggs et al., 2007; Dalziel, 2015; van Merriënboer et al., 2002). However, students as agents consciously and perhaps opportunistically make decisions on what, how, and when to engage in a particular range of learning activities (Winne, 2017). While teachers might think that a student will read chapter 2 in week 2, perhaps some students are already pre-reading materials from week 4, while other students may not have watched the introduction video of week 1.

A large body of educational literature in time management and procrastination has shown that students who are more capable of planning and managing their time for studying tend to perform better than students who procrastinate (Broadbent et al., 2015; Claessens et al., 2007; Kim et al., 2015). While previous studies in education often capture the time construct as a static trait through self-report questionnaires (Macan, 1994), there is a shortage of research exploring the dynamic temporal changes in learning behaviour in an authentic setting. LD provides a frame of reference of *what* and *when* teachers expect their students to study, and LA offers a realistic picture of *what* and *when* students study. Therefore, by having a better understanding of how much time students spent on respective learning materials and, more importantly for this study, when in time they studied these learning materials, this may enhance our intertemporal understanding of how students make complex study decisions.

Therefore, Study 4 will investigate the extent to which temporal aspects of student engagement align with LDs and how different engagement patterns influence academic performance.

- **RQ4.1** How does students' timing of engagement align with learning design?
- **RQ4.2** How does students' timing of engagement relate to academic performance?

2.4 Conclusion

Given the aforementioned gaps in the literature and the synergy between LA and LD, this thesis aims to understand how teachers design for learning from three perspectives: LD representations, teachers' perceptions, and students behaviours (Figure 3). Study 1 will examine how teachers design for learning over time based on data captured from LD representations. Study 2 will explore teacher's perceptions towards their own LD, towards the existing LD practices at the OU, and towards the potential of using LA to support their teaching practices. This will help to compare and contrast any similarities and differences between LD representations and the intentions of teachers. Study 3 will investigate the effect of LD on student behavioural engagement over time. This will reinforce the role of instructional context and pedagogy in LA research. Study 4 will dive deeper into the temporal process of learning behaviours at a fine-grained level. This study will identify the inconsistencies between teachers' LD and actual learning behaviour of students. The study will make a powerful case of how combining LA and LD could produce actionable insights. In conclusion, the multi-dimensional approach will allow me to examine the complexities of LD and triangulate results from multiple perspectives, which will increase the reliability of the findings.

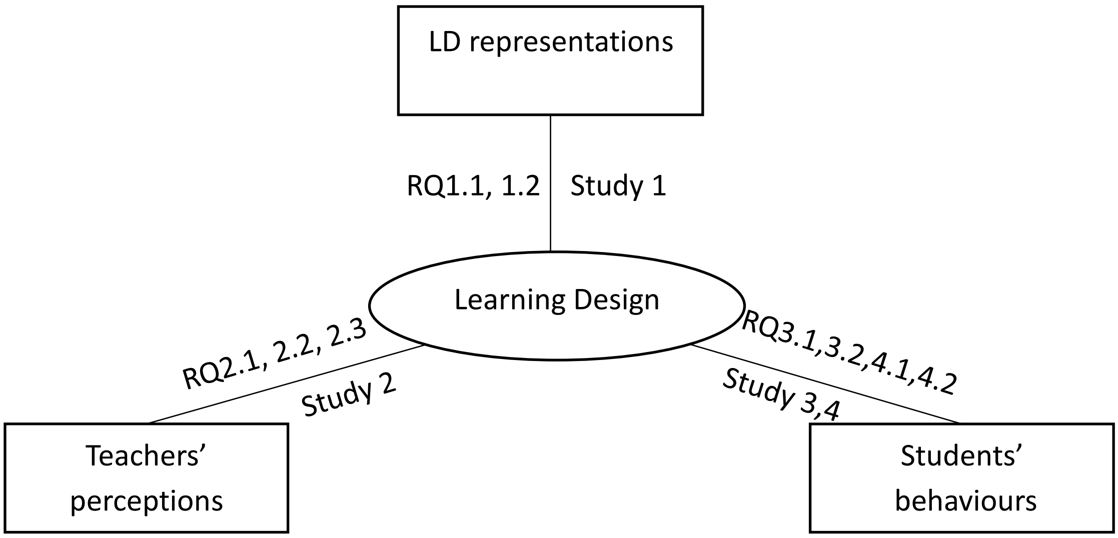

Figure 3. Understanding learning design from three perspectives

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Chapter 3 – Methodology

3.1 Introduction

This chapter describes the overarching methodologies and methods adopted in the four empirical studies, which are described in Chapters 4-7. Section 3.2 presents the research philosophy and justifications for the use of a pragmatic approach and mixed methods in this thesis. Section 3.3 provides an overview of the research design, study context, and instruments. Section 3.4 describes the rationale of each method incorporated across the four studies (i.e., network analysis, multilevel modelling, and semi-structured interviews). Finally, Section 3.5 discusses the ethical considerations applied in this research.

3.2 Research Philosophy

This thesis aims to investigate how teachers design their course and the impact of LD on student engagement in distance education by connecting LD with LA. Because of the interdisciplinary nature of both fields, it is essential to select appropriate methodologies and methods that align with the research questions and the philosophical underpinnings when designing research studies (Crotty, 1998). To understand the positionality of this thesis, it is important to discuss the role of a research paradigm (Kivunja et al., 2017).

In educational research, a research paradigm refers to a perspective, or thinking, or school of thought, or set of shared beliefs, that informs the meaning or interpretation of research data (Kuhn, 1962; Mackenzie et al., 2006). A paradigm comprises of three main elements: epistemology, ontology, and methodology (Twining et al., 2017). *Ontology* refers to the nature of truth (i.e., what is reality), while *epistemology* is concerned with the nature of human knowledge about truth (i.e., how do we know what reality is) (Mertens, 2014). *Methodology* is the broad term used to refer to the research design, methods, approaches and procedures used in an investigation that is well planned to find out something (Lincoln et al., 1985).

Three popular research paradigms in education are positivism, interpretivism, and critical paradigm (Crotty, 1998). A fourth paradigm which combines elements from these three is known as a pragmatic paradigm (Tashakkori et al., 1998). Table 10 summarises these four paradigms and their epistemology, ontology, and methodology.

Table 10 Comparison of popular research paradigms

Paradigm	Ontology	Epistemology	Methodology	Methods
Positivism	There is one single truth waiting to be found	Reality is measurable with valid, reliable tools	Quantitative	Experiments Surveys Statistical analysis
Interpretive / Constructivism	Realities are multiple and socially constructed	Reality must be interpreted through the lens of group members	Qualitative	Interviews Observation Case study Narrative
Critical	Realities are shaped by social, political, cultural, economic, ethnic and gender-based forces	Reality is socially constructed and must be interpreted through the lens of society	Qualitative	Interviews Observations Focus groups Journals
Pragmatism	Reality is the practical effects of ideas	Reality can be discovered by the best-suited method for each problem	Quantitative and qualitative (mixed methods)	A combination of any of the above

Based on (Kivunja et al., 2017; Lincoln et al., 1985; Mackenzie et al., 2006; Tashakkori et al., 1998; Twining et al., 2017)

Positivism is by far the most dominant research paradigm in the field of LA. For example, systematic reviews by Viberg et al. (2018) on 252 papers on LA in higher education from 2012 to 2018, and by Dawson et al. (2019) on 552 papers in LAK proceedings from 2011 to 2018 showed that most LA studies focused on measuring, quantifying, and modelling student characteristics and their behaviours using statistical methods. Positivistic LA researchers often use self-report measures (Tempelaar et al., 2015), trace data (Macfadyen et al., 2010), or physiological data (Dikker et al., 2017) as proxies of student characteristics and learning processes. Positivist LA research operates on the assumption that learning strategies, processes and learning outcomes might be captured and formalised through proxies generated from digital learning systems or validated questionnaires. The positivist paradigm is frequently adopted when the learning constructs can be quantified through established measurements and the priority of the research is generalizability (Cohen et al., 2002; Mackenzie et al., 2006).

However, in many circumstances, the investigated problems in education are complex and difficult to formalise. For example, LA adoptions and ethical issues are multifaceted, and consist of socially-constructed perceptions on what is considered as ‘effective’ and ‘ethical’ in LA (Ferguson et al., 2017; Griffiths, 2013). Therefore, qualitative approaches come from the interpretivism/constructivism, and critical paradigm (i.e., interviews, focus groups) are suitable for evaluating the impact of LA adoptions (Herodotou, Rienties, et al., 2019), or understanding ethical/privacy issues in LA

(Prinsloo et al., 2017). For example, the SHEILA (Supporting Higher Education to Integrate Learning Analytics) introduces a LA policy development framework based on interviews with 78 senior managers from 51 European higher education institutions across 16 countries (Tsai et al., 2018). The interpretivism paradigm is often used to gain in-depth understandings of a research phenomenon within a specific context (Cohen et al., 2002; Mackenzie et al., 2006).

Research in the field of LD is drawn from the social-constructivism paradigm (Dalziel et al., 2016; Lockyer et al., 2008; Maina et al., 2015). Conole (2012) argues that the underlying principles of LD are the concept of mediating artefacts (Conole, 2012), which were grounded in a constructivist perspective (Vygotsky, 1980) and activity theory (Engeström et al., 1999). The central idea of a constructivist is the notion that the process of cognitive development is contextually and socially bound. Thus, this recognizes that learning activities depend on the context within which they take place. For example, the use of Activity Theory highlights the relationship between different components embedded in the design process and its context (Engeström et al., 1999). Learning activities mediate between the users and the end goals. If these activities can be abstracted and represented in a meaningful and understandable way, there is a greater chance of them being picked up, used and adapted by others (Conole, 2012).

Each research paradigm has its own strengths and weaknesses. Positivists might overlook the social contexts and subtle nuances of educational phenomena, while interpretivist research is subject to criticism of generalisability and replicability (Creswell & Clark, 2017). If researchers fix themselves only on a single research paradigm, they might have to face certain compromises: generalised (i.e., the finding can be applied across contexts) versus contextualised (i.e., the finding account for its local context), hypothesis testing (i.e., was there a correlation) versus theory generating (i.e., why was(not) there a correlation), or personal biases (e.g., self-fulfilling prophecy, social desirability bias) versus systematic biases (e.g., sampling bias, measurement errors) (Cohen et al., 2002; Mackenzie et al., 2006).

Because this thesis revolves around the intersection of LA and LD, it requires methods from different research paradigms that are the most suitable for answering each respective research question. On the one hand, the exploration of LD and its relation to student behaviour (Study 1,3,4) can be captured through artefacts of learning activities and digital traces. On the other hand, teachers' perceptions of LD (Study 2) are influenced by both individual and social context. Therefore, the research questions called for the flexibility of a pragmatic approach with a mixture of quantitative and qualitative methods (Tashakkori et al., 1998). Pragmatism accepts that truths are multifaceted, and researchers should use the best-suited method to answer each research question (Tashakkori et al., 1998).

Although mixed-methods research is powerful, it can be challenging, expensive, and time-consuming for researchers to carry out because they demand mastery from a wide range of techniques (i.e., statistical and computational modelling, surveys design, qualitative analyses). A mixed-method design also requires a carefully thought-out research design so that both qualitative and quantitative elements can be harmonised together (Johnson et al., 2004). Last but not least, mixed methods can be opposed by "methodological purists" who contend that one should never mix methods from two different research paradigms (Twining et al., 2017).

This section has provided the justifications for adopting a mixed-method research design within a pragmatic research paradigm. The next section will describe the research design in more details.

3.3 Research Design

The overarching aim of this thesis is to understand how teachers design for learning in a distance higher education institution and the effect of LD on student engagement. To achieve this aim, I employed a case study approach as a research strategy for methodological exploration. According to Yin (2014), a case study is an empirical inquiry that investigates a phenomenon in depth within real-world context, where the boundary between the phenomenon (i.e., effect of learning design on student engagement) and its context (i.e., The Open University) is unclear, and may contain many variables. A case study research design is particularly powerful when the investigated phenomenon requires a collection and analysis of multiple data sources (e.g., learning design artefacts, teachers' beliefs, and students' behaviour). A case study goes hand in hand with a mixed-method research design, as they are both not assigned to a fixed ontological, epistemological or methodological position (Guetterman & Fetters, 2018). To integrate mixed-methods within a case study design, this thesis undertook a single, embedded case study approach that involves units of analysis that come from multiple levels (i.e., course level, teacher level, student level).

3.3.1 Study context

Given the aim of this thesis, which is to explore how teachers design their course and how LD impacts student engagement in distance education, the Open University UK (OU) was chosen as the study context of this thesis. Firstly, the OU is the largest academic institution in the UK and in Europe with 117,935 enrolled students in 2017/18[7]. The number of part-time students at the OU accounts for 23% of all part-time students in the UK[1]. As a pioneer in distance learning model since 1969, the OU offers more than 200 qualifications and 400 modules via a distance learning model, which involves the use of a VLE in conjunction with online and/or face-to-face tutorials with designated tutors. Furthermore, many distance learning institutions around the globe have been modelled after the OU adopting similar teaching and LD principles (Mittelmeier, Long, et al., 2018). Therefore,

[7] https://www.hesa.ac.uk/news/17-01-2019/sb252-higher-education-student-statistics/location

the OU is an ideal place for research in distance and online education because it increases the generalisability (i.e., large samples) and transferability (i.e., applicable in other distance learning settings) of the findings in this research project.

Secondly, the OU is one of the pioneers in researching and implementing LA initiatives at a large scale in the UK (Clow, 2013; Ferguson, 2012; Herodotou et al., 2017; Herodotou, Rienties, et al., 2019). For example, OU Analyse produces an early prediction of 'at-risk' students based on their demographic data and their interaction with Virtual Learning Environment (Kuzilek et al., 2015). The project was piloted in 2014 and now has been rolled out to a large number of 231 module teams and 1159 associate lecturers (ALs) at the OU (Herodotou et al., 2019). In addition, the OU has a rich database of its students including demographics, academic performance, course registration, and trace data of activities on VLE across hundreds of thousands of students since 1970s. Therefore, the OU provides a unique opportunity for LA researchers to address educational research questions at a large-scale, improving research external validity and generalisability.

Thirdly, the OU is also a leader in researching and supporting LD in online and distance learning environments (Conole, 2012; McAndrew et al., 2006; Sharples et al., 2016) . Compared to other universities, the OU module production process is longer and more complex. This process typically takes two to four years, involving multiple stakeholders with highly specialised skills in academic content writing, teaching, project management, media production and technical development (Cross et al., 2012). For example, the OULDI-JISC project from 2008-2012 aimed at implementing, evaluating and revising a range of LD tools, approaches and resources that had been developed for the enhancement of formal and informal curriculum design practice (Cross et al., 2012). A wide range of tools to support LD was created from this project, such as Compendium LD, Cloud works, Course Map, Activity Profile. A small number of studies at the OU have started exploring the synergy between LA and LD at a macro level (Rienties & Toetenel, 2016a, 2016b; Rienties et al., 2015; Toetenel et al., 2016a). This has laid out a foundation for my research project to build upon and to further explore the connection between LA and LD at a more fine-grained level.

Finally, while there are other distance online learning platforms such as edX, Coursera, Udacity, or Future Learn, the OU has the unique advantages as well as disadvantages of being a formal distance learning institution (McAndrew et al., 2013). OU students often register to pursue a long-term educational process that results in undergraduate and/or post-graduate degrees. Students are expected to pay tuition fees (approx. £5,000 per annum), to take part in examinations, and follow a fixed study schedule (i.e., by semester). In contrast, MOOCs are often offered for free or with a small fee without the constraint of a fixed schedule. Therefore, MOOCs attract a larger number of students compared to a formal distance learning institution such as the OU. However, the advantages of MOOCs come with a price, that is a low completion rate and the lack of information about students (Jordan, 2014, 2015).

To effectively compare LD and learning behaviour using LA, this research requires an environment which has a well-established LD practice, a wealth of relevant data about student characteristics and their behaviours, and a medium to high completion rate, which allows to analyse students behaviour and academic performance from the beginning to the end of a module. Therefore, the OU is arguably a well-fitted context for this research.

3.3.2 Research questions and studies

This research project comprises of four studies to address nine research questions, as summarised in Table 11. Study 1 aims at exploring the overall trends of LD at the OU through visualisations and network analysis of 37 LD representations over 30 weeks. The visualisation techniques help to explore common patterns and variations in LD over time, while the network analysis provides complementary visuals and metrics which accounted for the interactions between different types of learning activity. Although common patterns in LD can be identified from LD visualisations, there may be subtle nuances that could influence the teacher design process that requires an in-depth investigation from the teachers' perspectives, which is the motivation for Study 2.

Study 2 uses a qualitative approach to gain an in-depth understanding of the underlying driving factors behind the teacher design process and identify the affordances as well as barriers that teachers face when adopting LD tools at the OU. Study 2 comprises of 12 semi-structured interviews with module chairs, who hold the overall responsibility for the design process of a module. A more detailed description of the role of a module chair will be discussed in section 5.2.1. Study 2 and Study 1 complement each other for data triangulation purposes contributing to the overall understanding of LD at the OU. After laying out the foundation for understanding LD practices at the OU, this thesis will continue to investigate the impact of LD on student behaviour.

Study 3 examines the impact of LD on student engagement measured by time spent on VLE on a week-by-week basis in 37 undergraduate modules and their 45,190 students. Because the engagement patterns of students varied from module to module, a fixed-effect model was used in Study 3 to account for the heterogeneity between different LDs. Study 1,2,3 together aim to contribute to a holistic understanding of LD practices at the OU from three data sources: LD data, teacher perceptions, and student behaviour.

Table 11: Overview of research questions and methods

Study	Research Questions	Sample	Instruments	Methods
Study 1	**RQ1.1** What are the temporal characteristics of learning design? **RQ1.2** How do different types of learning activity interact with each other?	37 modules over 30 weeks	LD data	Visualizations Network analysis
Study 2	**RQ2.1** What are the driving factors behind teachers' design decisions? **RQ2.2** What are the barriers and affordances of learning design adoption at the OU? **RQ2.3** How do teachers make use of feedback on their module to support learning design?	12 teachers (module chairs)	Interview questions	Semi-structured interview
Study 3	**RQ3.1** How do learning designs influence student behavioural engagement over time? **RQ3.2** How do learning designs influence student satisfaction and pass rate?	37 modules and 45,190 students	LD data VLE trace data	Fixed-effect modelling
Study 4	**RQ4.1** How does students' timing of engagement align with learning design? **RQ4.2** How does students' timing of engagement relate to academic performance?	1 module, 387 students, replicated over two semesters	LD data VLE trace data	Multi-level modelling

Finally, Study 4 takes a further step to investigate to what extent student engagement aligns with teachers' LD and different engagement patterns affect academic performance. Study 4 will analyse fine-grained trace data on a daily basis of 387 students in one module over two semesters. Given the hierarchical and longitudinal structure of the data (i.e., learning behaviours were nested within students), a mixed-effect (multilevel) model was used to account for the random variance across individuals.

The four studies together make up the whole thesis by triangulating data from three different sources: LD representations, teacher perceptions, and student behaviour. Triangulation is one mean to validate, challenge, or extend existing findings using multiple alternate perspectives (Denzin, 2007). In this thesis, two types of triangulation were carried out: data triangulation and methodological triangulation. Data triangulation entails obtaining evidence from multiple sources, or at different time points, or under different conditions (Denzin, 2007). In this thesis, data were collected from three main sources at three levels of granularity.

The first data source was learning design artefacts collected at a module level (i.e., activity types) and module characteristics (i.e., disciplines, number of credits, length, workload). The second data source was generated at a teacher level, which comprised of interview transcripts that reflected their experience, beliefs, and opinions about the course design. The third data source was generated at a student level, including students' individual characteristics (i.e., age, gender, grades) and their learning activities (i.e., trace data on VLE). For instance, Study 1 extrapolated common trends and patterns in learning design across 37 modules. Insights from Study 1 were then combined with the underlying perspectives of teachers who were responsible for designing those modules. Finally, data from students enrolled in those modules were analysed to understand the effects of these learning design decisions on students' engagement and their academic performance. The data triangulation process also accounted for different temporal dimension, such as daily, weekly, to aggregated data per course (Figure 4).

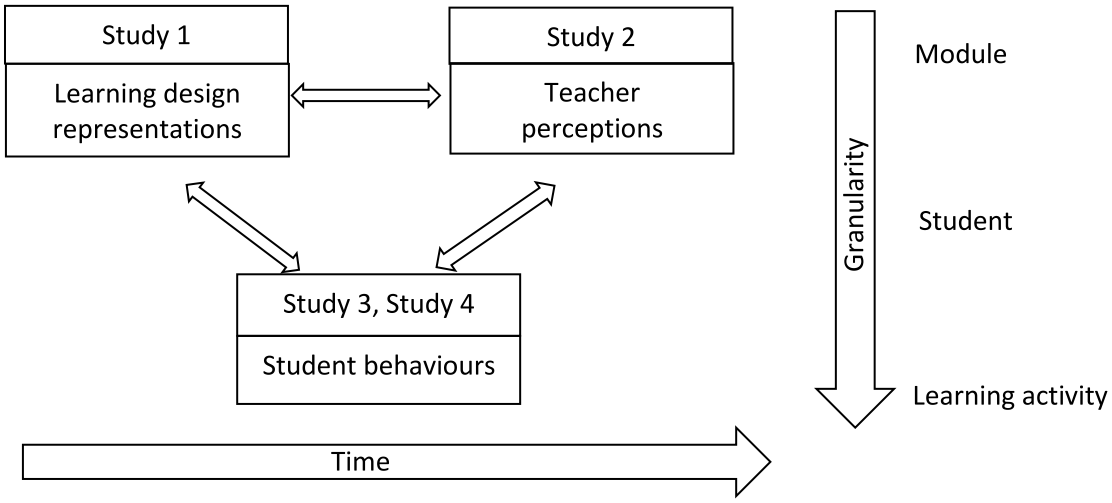


Figure 4. An overview of the research design

Methodological triangulation in this thesis was achieved by combining more than one method to collect or analyse data. This thesis employed a wide range of quantitative methods (e.g., network analysis, multilevel modelling) and qualitative method (e.g., semi-structured interviews). The following sections will describe in detail the key variables used in this thesis.

3.3.3 Learning Design at The Open University

As described in Chapter 2, the field of LD aims at developing a descriptive representation of learning and teaching practices. Capturing and quantifying pedagogical practices is challenging, to say the least. At the OU, each new module goes through a mapping process, which maps out all learning activities and their estimated time to complete the activities. Learning activities are categorised based on the learning activity taxonomy originally developed by Conole et al. (2008), which has subsequently been further fine-tuned and adjusted over time based upon both practical experiences as well as LD research (Toetenel et al., 2016a, 2016b) (Table 12).

Table 12 Learning activity taxonomy

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.

Retrieved from *Conole (2007)*

Assimilative activities refer to tasks which require student's attention to information. These include watching lecture video, reading the text, listening to an audio file, etc. *Finding and handling information* activities implies, for example, searching and filtering for relevant literature in a particular topic on the internet. *Communication* activities refer to a range of practices to communicate such as posting in a discussion forum and replying to peer comments. *Productive* activities represent the construction of an artefact, such as writing a summary or resolving a problem. *Experiential* activities provide students with opportunities to apply theories in a real-world setting such as case study, or field trip. *Interactive/adaptive* activities encourage students to apply what they learned in an experiential environment or interacting with a simulation. Finally, *assessment* activities evaluate the student's understanding such as writing through the construction of an essay, exam or making a presentation (Conole, 2012; Conole et al., 2008).

For each learning activity, an estimation is made for how long it would take an average student to complete that activity. This estimation is usually determined by the module team and being embedded in the module guide on the VLE as a guidance for students' study time allocation (Figure 5). If the time estimation is not explicitly stated in the module guide, it will be determined using agreed conventions for study speed and amount of time allocated to studying figures, tables, images, audio and video within module materials[8]. Study speed can be set at low (35 wpm), medium (70wpm) or high (120wpm), depending on the type of material, the level of study, or other influencing factors such as concept density. Study speed assumes that as well as reading the text, students will take additional time to absorb and reflect on what they read. For example, an introductory-level reading of 2000 words would take approximately 2000/120 = 17 minutes. The time estimation of each learning activity was aggregated at a weekly level (i.e., estimated workload per week). The workload of each module was restricted by its number of credits, with each credit equates one hour of studying. For example, a 30-credit module requires 300 hours of learning or 8-9 hours per week, and a 60-credit module requires 600 hours of learning or 16-18 hours per week.

Figure 5: Time estimation of learning activity in a module guide

Activity 3.3

Spend approximately 35 minutes on this activity.

The Open University provides guidance on a number of study skills on the StudentHome website. You are encouraged to refer to these guidance notes and exercises as and when it seems useful to you. However, from time to time you will be explicitly directed to one of these OU study skills sessions as part of one of the activities on B100. This is because much of the generic guidance available in the sessions is very relevant to studying B100 and it would be an unnecessary doubling of effort to recreate very similar guidance here, specifically for B100. Also, by linking to the generic study skills pages you will get an idea of what else is available there that may be useful to you at some point. This activity on note taking is one of those where you are encouraged to work through a generic study skills session before you return to the B100 website to complete the activity with some B100 specific material.

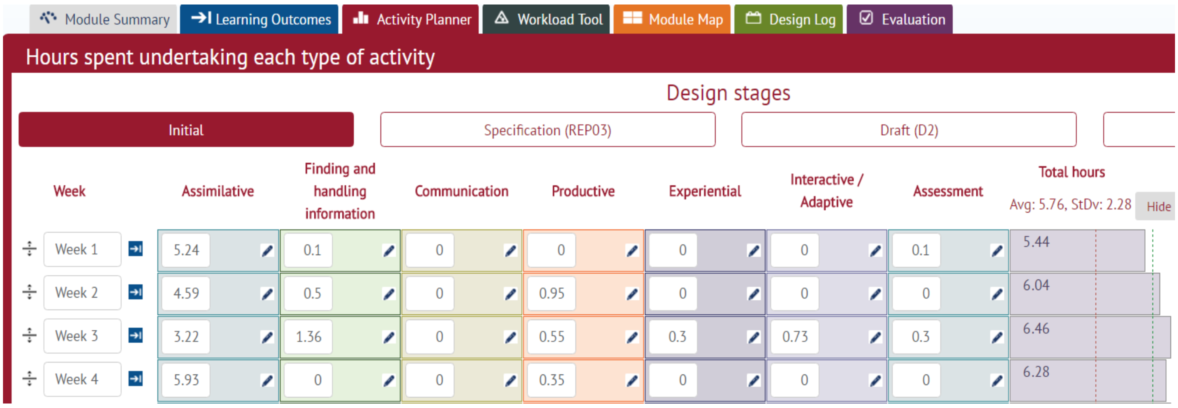
Source: A screenshot from the OU online module guide at www.learn2.open.ac.uk

When using data to compare module design across disciplines and modules, according to previous work (Rienties & Toetenel, 2016b; Toetenel et al., 2016a) it is important to classify learning activities in an objective and consistent manner. In particular, each module goes through a mapping process by a module team which consists of an LD specialist, an LD manager, and faculty members. This process typically takes between 1 and 3 days for a single module, depending on the number of credits, structure, and quantity of learning resources. First, the learning outcomes specified by the module team were captured by an LD specialist. Each learning activity within the module's weeks, topics, or blocks was categorised under the LD taxonomy and stored in an 'activity planner' – a planning and design tool supporting the development, analysis, and sharing of LD (Figure 6). Next, the LD team manager reviews the resulting module map before the findings are forwarded to the faculty. This provides academics with an opportunity to comment on the data before the status of

[8] http://learning-design.open.ac.uk/conventions

the LD is finalised. To sum up, the mapping process is reviewed by at least three people to ensure the reliability and robustness of the data relating to LD.

Figure 6. Activity Planner tool



Source: A screenshot from the OU Activity Profile at www.learning-design.open.ac.uk

There are several strengths and weaknesses of the current mappings based on the OULD taxonomy (Table 13). On one hand, the representations and visualizations of LD using these seven categories could help educators gain an overview of the elements embedded in their LD, and their relative proportions. The project report of the OULDI (Cross et al., 2012), together with several empirical studies based on the OULD taxonomy have indicated some benefits of this approach in supporting teachers' pedagogical decisions (Clifton, 2017; Toetenel et al., 2016a) and predicting student engagement, satisfaction, and pass rates (Rienties & Toetenel, 2016b).

For example, in a study of 148 LDs by Toetenel et al. (2016b), the introduction of a systematic LD initiative consisting of visualization of initial LDs and workshops have been shown to help teachers develop a more balanced LD. 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 (2016b) revealed relations between LD activities and VLE behaviour, student satisfaction, and retention. The findings showed that taking the context of LD into account could increase the predictive power by 10-20%. Moreover, the OULDI approach has also been adopted by external institutions such as the University of South Africa (Mittelmeier, Long, et al., 2018; Mittelmeier et al., 2019).

On the other hand, compared to other LD representation frameworks as discussed in section 2.2.2 (Anderson et al., 2001; Bloom, 1956; Laurillard et al., 2018; Law et al., 2017), the OULD taxonomy neither captures specific elements nor the sequential order of the learning activities in the LD. Furthermore, the collapsed categorizations of activities at a macro level could inhibit the interpretation of the results. For instance, summative and formative assessments are collapsed under one general category "assessment activities". Moreover, there could be overlaps between these activities. For example, when students carry out finding and handling information activities, they also include readings (assimilative activities). Therefore, the interpretations of these learning activities are subjective to how data are coded by respective individuals, potentially leading to individual bias.

Furthermore, the time estimation of each learning activity does not necessarily reflect the actual time spent by students. The suggested workload is based on subjective estimation of the module team on how long they think each activity should take for an average student to complete. This estimation works well for structured activities such as readings or watching videos as they have some formal metrics (e.g., words per minute, length of a video). However, the estimation might be less accurate for unstructured activities such as discussion forums or exam preparation. Last but not least, the OULD taxonomy only captures the output of the LD process (i.e., module guide, artefacts of learning activities) while less focus on the underlying factors behind the LD process (e.g., teacher experience, institutional policies).

Table 13. Advantages and disadvantages of OULDI mappings

Advantages	Disadvantages
Provide an overview of LD at a macro level	Overlap or oversimplifications of learning activity categories
Help teachers reflect on the workload and types of learning activity	The accuracy of time estimation varied across different types of learning activity
Provide an estimate of study workload based on teachers' suggested time spent	Do not reflect actual time spent by students
Have been shown to be correlated with student engagement, satisfaction, and performance.	Only capture the output of the LD process, do not take into account the underlying pedagogies

Based on (Clifton, 2017; Cross et al., 2012; Rienties et al., 2017; Rienties & Toetenel, 2016b; Toetenel et al., 2016a, 2016b)

To address the current limitations, two approaches are proposed. Firstly, in line with recommendations of Lockyer et al. (2013); Persico et al. (2015), interviews with teachers (Study 2) will be conducted to triangulate LD visualisations with teacher's perceptions to explore the driving factors behind their design decisions and to critically reflect upon the potential affordances and barriers when engaging in LD practices at the OU. Insights from these interviews will help me to unpack the LD at a more fine-grained level, and gain a better understanding of the underlying factors that influenced LD decisions. At the same time, the results from interviews will provide learning designers with feedback on how to further improve the OULD taxonomy and measurements.

Secondly, the measurement of LDs will be tested against student learning behaviour using LA (Study 3, 4). In particular, I will test to what extent the number of hours allocated for each learning task (i.e., how much time students are expected to spend) align with how much time students actually spend on the corresponding task. For example, if reading a book chapter was mapped as an activity of 2 hours by the OULDI framework, then to what extent students actually spent this amount of time on this book chapter. Therefore, this step is crucial to identify potential overestimation or underestimation of the workload estimates generated by the LD mappings. The measurement of student engagement is discussed below.

3.3.4 Student behavioural engagement

Academic engagement is a multi-dimensional construct ranging from behavioural engagement, emotional engagement, and cognitive engagement, (Azevedo, 2015; Kahu, 2013; Sinatra et al., 2015; Trowler, 2010). Student academic engagement in this thesis is operationalised from a behavioural perspective, which viewed engagement as involvement in one's own learning and academic tasks through displays of effort, persistence, behavioural aspects of attention, and self-directed academic behaviour (Sinatra et al., 2015). The link between student behavioural engagement and academic achievements has been robustly established in educational literature (Kahu, 2013; Trowler, 2010).

Educational researchers possess a wealth of measures from which to choose to capture, analyse, and infer different aspects of engagement, such as think-aloud protocols, eye-tracking (Miller, 2015), log-files (Gobert et al., 2015), facial expressions (D'Mello et al., 2017), physiological sensors (Dikker et al., 2017), self-report questionnaires (Pekrun et al., 2011; Pintrich et al., 1993), or classroom observations (Ryu et al., 2015). The choice of measurements should align with the theoretical conceptualisations of engagement and the learning context (Azevedo, 2015). For example, eye-tracking methods can provide a precise measurement of attention allocation and yield several indices of cognitive processing strategies. However, they do not provide direct evidence about metacognitive, affective, and motivational processes. On the other hand, facial expressions and physiological sensors can detect changes in the emotions of a student while engaging in academic tasks. However, they are not suitable to understand the cognitive processing of engagement, and typically these approaches are difficult to scale beyond the lab environment.

In this research project, trace data of student learning activities in a VLE (e.g., Moodle) were used as a proxy of student engagement, which is justified by the following reasons. Firstly, this thesis focuses on the behavioural aspect of engagement, in which time-on-task has been consistently shown to significantly correlated with academic performance and self-report measures of engagement (Jovanović et al., 2017; Rienties & Toetenel, 2016b; Tempelaar et al., 2017). Secondly, the context of this thesis is a distance learning institution. In this context, most learning activities are designed for and on a digital learning platform (e.g., Moodle), which make log-files suitable to capture and represent learning engagement. This is different from a face-to-face or blended learning context, in which most learning activities commonly happen outside of the LMS. Thirdly, the research questions of this thesis emphasise the temporal aspect of the behavioural engagement, such as when students engaged and for how long. While other measurements capture engagement at one specific point in time (i.e., surveys) or a short period of time (i.e., eye-tracking, sensors), trace data allow researchers to unpack the temporal changes in the behavioural engagement at different levels of temporal granularity (i.e., seconds, days, weeks, years). Finally, trace data supports the data triangulation process with LD data, by detecting which learning activity/material that students engage with and for how long.

While trace data is one of the most common proxies of engagement in LA research, they should be treated with caution (Table 14). From a measurement perspective, as pointed out by previous research (Kovanovic et al., 2016), this metric could be problematic due to (1) the inability to differentiate between active time and non-active time (e.g., students leave the respective web page open and go for a coffee), and (2) the last click of the day is followed by a click next day, which makes the duration excessively long. Any attempt to set an arbitrary cut-off value would pose a threat in underestimating or overestimating of the actual engagement time. Furthermore, trace data are not representative of the whole learning process, as many self-regulated learning activities happen outside the LMS, such as searching for information on Google, writing essays in Word, or taking notes.

Therefore, from an interpretation perspective, the measurement of time-on-task based trace data cannot guarantee that students are cognitively engaged with the tasks at hand. For example, students could leave their internet browser open while going for a break, or be distracted with Facebook. Even if students are actively engaging with the task, it is difficult to infer why students do certain activities. For example, a long duration of time spent on task could mean that students are doing well and enjoying the task, or struggling to understand the concept.

Finally, trace data are not informative when they are taken out of context. For example, students in course A may exhibit a higher level of engagement than students in course B. An alternative explanation could be that course A was designed with more online interactive activities, whereas course B was designed with more off-line self-study activities, such as writing essays. Therefore, the differences in the level of engagement reflect the differences in how the learning activities were designed, and whether the traces of these activities can be captured through VLE. This example reinforces the importance of integrating LD data to provide the pedagogical context to better interpret digital traces of student engagement.

Table 14 Advantages and disadvantages of VLE trace data

Advantages	Disadvantages
A large volume of real-time data	Cannot capture activities occurred outside of VLE
Capture learning behaviour over a long period of time	Outlier problems
Work best in an online learning environment	Less suitable for blended or offline learning

This section has explained and justified the choice of study context and the measurements used in this thesis. The next section will describe the methods used to analyse the data and its relation to the research questions.

3.4 Research Methods

3.3.1 Network Analysis

Study 1 used a combination of visualisation and network analysis to explore the interplay between different types of learning activity. Social Network Analysis (SNA) is defined as the study of relationships among actors that interact with one another in a network structure (Wasserman et al., 1994). SNA is a commonly used technique in education and social science to study the network structure between people and entities (Cela et al., 2015; Dado et al., 2017). For example, a common application of SNA in education is the study of group formation between students. Rienties et al. (2018) used SNA to examine whether it is better for students to invest in social relations in groups to learn and enhance academic performance or to (continue to) invest in social relations outside groups. Wise et al. (2018) used a mixed method of SNA and qualitative analysis to compare social relationships and the underlying interactions they represent in forum discussions related and unrelated to the learning of course content.

A network is defined by actors (i.e., nodes) and by relations (i.e., edges, ties) (Figure 7). In social sciences, an actor is usually referred to a person although it can be an object, a group or an organisation. A tie exists when two actors are connected (Borgatti et al., 2002; Wasserman et al., 1994). For example, students can be considered actors within a network – a school. A tie occurs when two students establish a connection such as talking to each other. A tie could be directed (e.g., Student A talks to student B) or non-directed (e.g., there exist some communications between students A & B). The relationship between two actors/students can be categorised into either binary (connected/not connected) or on a continuum (e.g., from a weak to strong tie) based on the frequency of communication. A network that consists of actors belonging to the same type (e.g., students) is called a one-mode network. A network can also contain two sets of actors (e.g., students, classes), also known as a two-mode network, and ties only exist between actors from different sets (e.g., students only know each other by joining the same class).

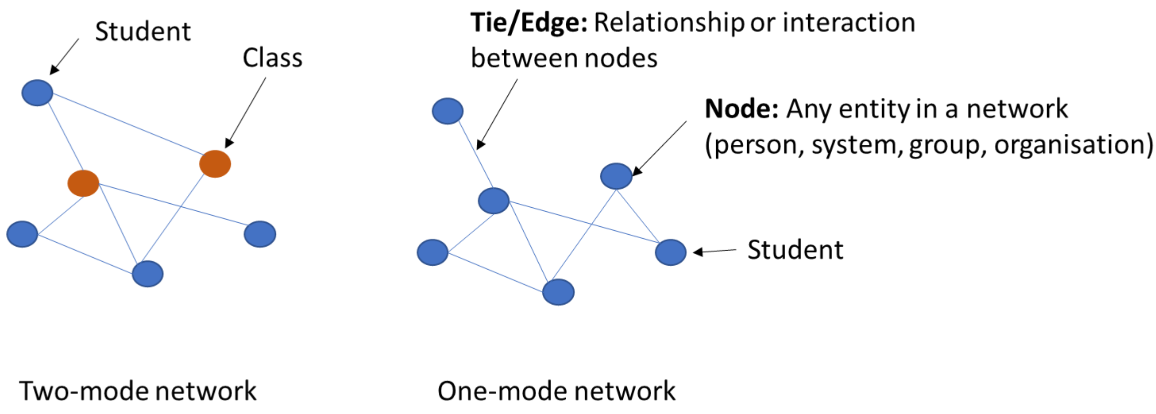


Figure 7. An example of social network analysis

Although many scholars have used SNA to study the social relations amongst students, little attention has been paid to the network structure of learning activities. As pointed out by Hora et al. (2013), learning activities do not operate in isolation but instead interlink as a result of a complex and dynamic designing process. In LD, teachers consider multiple factors such as course content and the relations with other previous and subsequent learning activities to ensure a coherent structure and effective learning process for students (Bennett et al., 2015; Dalziel et al., 2016). For example, an hour of reading is followed by 20 minutes discussion in an online forum and 20 minutes multiple-choice questions. The number of combinations of different types of learning activity is perhaps indefinite, and vary across different modules/teachers. Thus, focusing on analysing only one type of activities in isolation might obscure the complexities of the design process. Therefore, network analysis may be a suitable tool to model the inter-relationships of different learning activities in each LD. I used the term *network analysis* instead of *social network analysis* because in this thesis I focused on the relations between educational entities (i.e., designs of learning activities) instead of social relationships amongst students. A detailed description of the analysis procedure is provided in Chapter 4 – Study 1.

Despite its advantages, SNA has some limitations. Firstly, SNA studies are unlikely to capture the full extent and influence of all relevant factors. In this context, the learning activity taxonomy determines the number of nodes in a network of learning activities. There could be missing links between activity types that are not included in the theoretical framework. For example, both summative and formative assessments were collapsed under the same assessment category. Secondly, SNA might oversimply the actual relationship existed between two actors by categorising them into binary or undirected relations. In addition, the richness of information that flows between two actors is not captured in SNA. For example, SNA can visualise the frequency and direction of forum messages from one student to another, but the messages' content is not presented. Thirdly, as with most quantitative approaches, SNA is unable to answer why teachers design and combine different types of activities the way they do.

3.3.2 Semi-structured Interviews

While Study 1 uses a range of visualisations and network analysis to identify common LD patterns across a large number of modules, it cannot capture the contextual nuances of the design process, such as teacher pedagogy, institutional policies, or characteristics of learning environments (Bennett et al., 2015; Bennett, Agostinho, et al., 2017; Bennett et al., 2018). Study 1 can answer the *what* question (i.e., what has been designed) but not the *how* and *why* questions (i.e., how and why teachers designed the way they did). This is the key goal of Study 2: to gain an in-depth understanding of the underlying factors that influenced the LD process and to triangulate quantitative findings from Study 1. Therefore, Study 2 requires an analysis of teacher perceptions and reflections on the LD process at the OU through in-depth qualitative interviews.

Qualitative interviews are a commonly used method in educational research that allows researchers to develop in-depth accounts of experiences and perceptions of individuals. By collecting and transcribing interview talk, the researcher can produce rich empirical data about the lives and perspectives of individuals (Cousin, 2009). The structure of the interview and the design of the questions will influence the depth and freedom with which a participant can respond. Broadly speaking, there are three main types of interview designs: structured, semi-structured, and unstructured interviews (Brinkmann, 2014; Cousin, 2009; Williamson, 2018).

Structured or standardised interviews allows the researcher to ask each participant the same set of questions. This format makes it easy to compare respondent answers and can be replicated on a large scale, such as the UK Household Longitudinal Study[9]. However, structured interviews are not flexible as the interview schedule must be followed in a strict order and it does not provide in-depth insights into a phenomenon (Williamson, 2018). On the other hand, semi-structured and unstructured interviews are more flexible as questions can be adapted and changed depending on the respondents' answers (Williamson, 2018). This is important for this research because LD is heavily influenced by both individual and contextual/political factors.

For example, from a series of 30 interviews with educators across 16 Australian higher education institutions, Bennett et al. (2015) identified three key influences on teacher design decisions: student-related factors (student profile, learning goals, feedback), teacher-related factors (prior experience, pedagogical belief, self-belief), and contextual-related factors (colleagues, accreditation, institutional requirements, department requirements, resources). Therefore, semi-structured interviews offer opportunities to uncover hidden issues and subtleties in the LD process. At the same time, this nuanced analysis of teacher perceptions helps triangulate and confirm findings from

[9] https://www.understandingsociety.ac.uk/

Study 1. Both studies complement each other by providing a macro-level analysis at the module level (top-down) and micro-analysis at the individual teacher level (bottom-up).

However, there are some caveats of qualitative interviews that should be acknowledged. Firstly, the appearances and behaviours of the interviewer might bias how participants respond, so-called interviewer effect. Factors such as age, gender, race, occupation can contribute to this bias. There is also a risk of response bias as participants might not be completely honest, or present themselves in a social-desirable manner. To minimise these biases, I have made the motivation and rationale of my study explicit to the participants about, as well as my neutral stance as an independent PhD researcher with neither affiliation with the OU management nor the LD team. The participants were also reassured about the confidentiality of their responses with an explicit consent form and verbal confirmation at the beginning of each interview.

Secondly, because the qualitative analysis is an interpretive process, there might be room for mis-interpretation or self-fulling prophecy when coding the interview transcripts. To overcome this limitation, as per suggestions from literature in qualitative research method (Cohen et al., 2002; Creswell & Poth, 2017) and previous studies in LD (Bennett et al., 2015; Bennett, Agostinho, et al., 2017; Bennett et al., 2018), a random selection of the qualitative data was coded individually by two members: the primary researcher (myself) and another member from the supervision team. The codes were then compared and discussed to ensure the consistency and accuracy of interpretation.

Finally, qualitative studies are often subject to criticisms regarding the generalisability of the study due to the small sample size. This weakness is in part offset by Study 1 and Study 3 which carried out large scale analyses on 37 modules and 45,190 students. The next section will discuss the quantitative methods of Study 3 and 4.

3.3.3 Fixed-effect modelling

Study 1 and Study 2 lay the foundation of understanding LD in this thesis. Study 3 takes a further step to examine how LD decisions influence student learning behaviour. While there have been a few studies exploring this relation between LD and student behaviour (Gašević et al., 2016; Rienties & Toetenel, 2016a, 2016b; Rienties et al., 2015), their analyses based on linear regression have not taken into account the heterogeneity between modules. This is important because the effect of LD on student behaviour can vary from modules to modules, as shown in (Gašević et al., 2016). Given the panel data set in Study 3 (multiple modules over multiple weeks), a fixed-effect model was chosen to analyse the relations between LD and student behaviour because it accounted for the differences between modules.

To help readers understand the advantages of a fixed-effect regression model, I will compare it to a traditional linear regression model. A simple linear regression quantifies the relation between an independent variable X and a dependent variable Y, which can be formalised as follows:

$$Y_i = \beta_0 + \beta_1 * X_i + \varepsilon_i$$

Where

- Y_i is the dependent variable of subject i
- β_0 is the intercept of the regression line
- β_1 is the coefficient of X_i meaning how much Y change if X changes
- X_i is the independent variable of subject i
- ε_i is the residuals/error terms

Take an example where a simple linear regression is run between academic performance and student engagement, assuming the data are taken from multiple modules over multiple time points. Notice that in linear regression, the participants are treated as they belong to a homogenous sample while the heterogeneity between modules and time points is ignored. A fixed-effect regression overcomes this by accounting for the fact that the effect of engagement on academic performance varies between modules. Examples of these fixed effects of modules include level of study, number of credits, or disciplines. A fixed-effect model can be formalised as follows:

$$Y_{it} = \beta_0 + \beta_1 * X_{it} + \varepsilon_{it}$$

Where

- Y_{it} is the dependent variable of subject i at time t
- β_0 is the intercept of the regression line
- β_1 is the coefficient of X_i meaning how much Y change if X changes
- X_{it} is the independent variable of subject i at time t
- ε_{it} is the residuals/error terms

Figure 8 illustrates the difference between linear regression and a fixed-effect model. In a fixed-effect model, a regression line was fit for each group of students according to the module they enrolled whereas a linear regression treated all students the same.

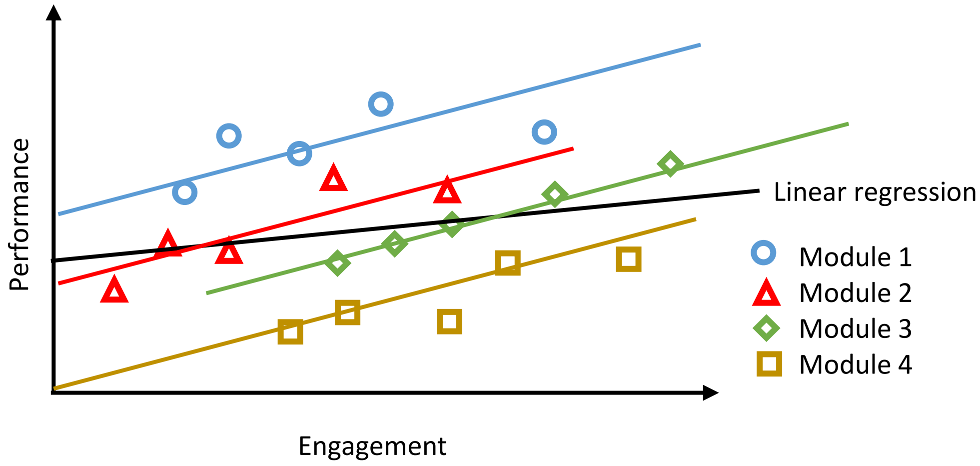


Figure 8. Linear regression versus fixed-effect regression – a hypothetical example

Because Study 3 collects data from both module level (i.e., LD mappings) and student level (i.e., behavioural engagement) over multiple weeks, fixed-effect models will be used to account for the unobservable heterogeneity of the data. A limitation of fixed-effect models is that all time-invariant factors of modules were absorbed in the intercept β_0, which makes it difficult to isolate the effect of time-invariant variables. For example, the level of study was already accounted by the intercept. Therefore, it is not possible to isolate the effect of the level of study in a fixed-effect model.

3.3.4 Multi-level modelling

Study 4 investigates the relations between the timing of engagement, LD, and academic performance. While Study 3 accounted for the heterogeneity between modules and time, Study 4 took a step further to account for the differences at the student level. The hierarchical structure of the dataset (i.e., students are nested within modules) calls for the use of a multilevel model. Multilevel modeling, also often known as random-effect or mixed-effect model, is a well-established method to analyse hierarchical and longitudinal data in social sciences (Goldstein, 2011). Education presents an obvious example of a hierarchical structure, with students (level 1) nested within courses (level 2), as indicated in Figure 9.

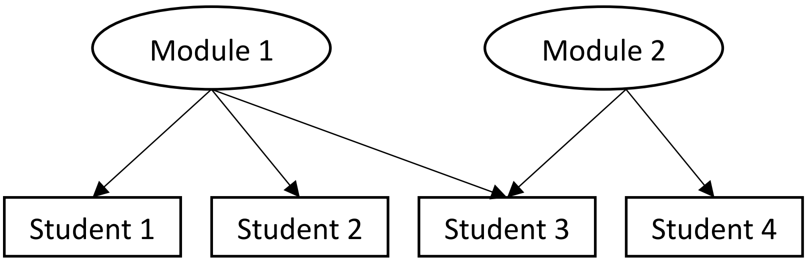


Figure 9: An example of hierarchical data in education

A traditional approach to the analysis of these data would be to carry out an ordinal least squares (OLS) regression with student engagement as a predictor and grade as an outcome. For example, Macfadyen et al. (2012) reported positive correlations between LMS activities and course grade using data of 95,132 undergraduate student enrolments in LMS-supported courses. In OLS regressions, all test outcomes from all students are assumed to be independent. However, when individuals form clusters, we might expect dependencies between different levels of the data. For example, the effect of students' engagement on academic performance might be influenced by both individual factors (i.e., prior knowledge, demographics) and contextual factors (i.e., course level, number of credits, discipline).

Therefore, using OLS regressions leads to smaller standard errors than true standard errors, which in turns produce misleading conclusions (i.e., conclude a significant effect while they might just be random variations). For example, Gašević et al. (2016) examined the effect of instructional condition on the prediction of academic success of 4143 undergraduate students in nine blended-learning courses. Their findings suggest that the lack of consideration for instructional conditions can lead to an over or underestimation of the effects of LMS behaviour on academic performance. To illustrate this problem, Figure 10 presents a hypothetical example of the difference between an OLS regression versus a random-slope multilevel model. It is evident that our estimations can be biased if we ignore contextual factors. To simply translate to educational research, the effect of engagement on learning outcome is influenced by the context in which learning occurs.

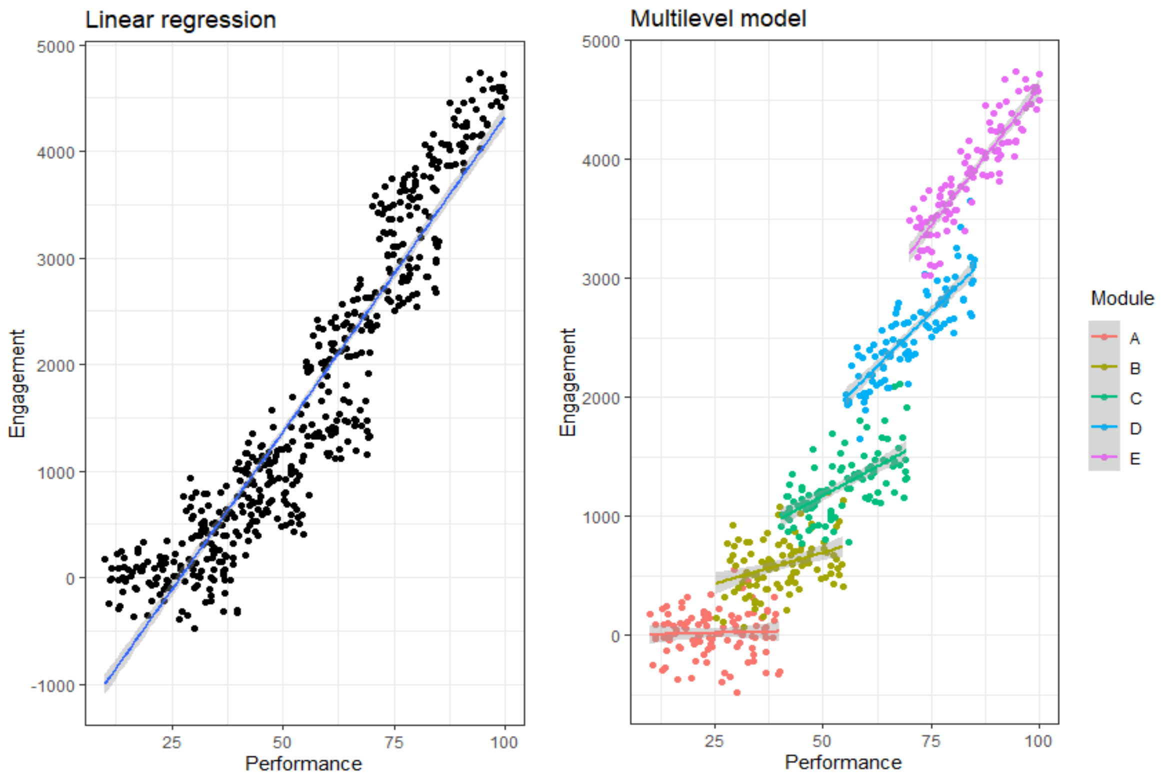


Figure 10: Linear regression versus multilevel model – a hypothetical example

Another application of MLM is the analysis of longitudinal data (i.e., VLE engagement over time are nested within students). The advantages of MLM compared to the traditional repeated-measures analysis of variance (RM-ANOVA) are its flexibility in handling missing data and variable timing of data collection. For example, students might be active on the VLE on day 1, inactive on day 2, 3, and then active again on day 4. This goes against the assumptions of RM-ANOVA which requires a fixed timing of data collection (i.e., every day, or every 2 days).

Given the research questions (RQ4.1, 4.2) and the hierarchical nature of the dataset in this research project, MLM is the most suitable method. Firstly, MLM accounts for heterogeneity across modules when examining the effect of LD on the timing of engagement. Secondly, MLM is an extension of a fixed-effect model that accounts for individual differences when examining the effect of longitudinal VLE engagement on academic performance (RQ4). Finally, my data fit with MLM requirements as they consist of numerous VLE activities nested within thousands of students across multiple modules and presentations. More technical details will be discussed in the subsequent studies.

There are some caveats of MLM and statistical modelling in general (Goldstein, 2011). As with any observational research, statistical inferences are limited to correlations only. In other words, a statistically significant effect could be found between two variables. However, I cannot make any causal inference based on the findings. For example, a positive and statistically significant relationship between student engagement and academic performance can be interpreted either as engagement causes performance (e.g., students study hard, therefore achieve higher grade) or performance causes engagement (e.g., high-performing students tend to study hard). Furthermore, observational data are open to interpretation and therefore the consistency between individuals varies. For example, a lack of engagement on VLE can be either interpreted as inactive (i.e., students did not study during that period of time) or studying in other platforms (i.e., students study offline or researching literature on google).

In summary, the interdisciplinary and multifaceted nature of this thesis requires a mixed-method design to address the RQs in a comprehensive and appropriate manner. The thesis comprised of four carefully designed empirical studies with a mix of qualitative and quantitative elements from multiple sources (i.e., module, teacher, student) that allow for data triangulation and complement each other strengths and weaknesses. The next section will outline the ethical considerations of this thesis.

3.5 Ethics

Ethics are quintessential in any research project involving the collection of data from human participants. Research in education must adhere to a set of published guidelines such as the British Educational Research Association's Ethical Guidelines[10] or the British Psychological Society 's Code of Ethics and Conduct[11] to ensure explicit consent from participants and ethical use of their data. In the field of LA, there have been numerous guidelines and checklists for ethical practices of institutions when implementing LA. For example, Sclater (2016) present a code of practice for LA [12], developed by JISC. Drachsler et al. (2016) introduce a 'D-E-L-I-C-A-T-E' checklist for researchers, policymakers, and institutional managers to facilitate a trusted implementation of LA. Prinsloo et al. (2017) explore the moral and legal basis for the obligation to act on the analyses of student data through two case studies from the Open University UK and the University of South Africa.

The issue of ethics is even more salient in LA research when student data are automatically collected by digital systems on a large scale. On the one hand, traditional educational research requires informed consent from participants for their data to be used in research. For instance, the OU Ethics Principles for Research Involving Human Participants[13] state that "Except in exceptional circumstances, where the nature of the research design requires it, no research shall be conducted without the opt-in valid consent of participants." and that "Participants ... have a right to withdraw their consent at any time up to a specified date". On the other hand, when registered at the OU students gave their consent for their data to be used, as part of the operational research to "identify interventions which aim to support students in achieving their study goals"[15] and the OU makes it explicit in its Learning Analytics Ethics Guideline that "it is not possible, at present, to have your data excluded". As a result, there seems to be a hidden 'ethical waiver' for learning analytics research within institutions (Griffiths, 2017).

The ethical considerations in this research project is informed by the vast amount of literature on ethical use of LA (Drachsler et al., 2016; Prinsloo et al., 2017; Sclater, 2016), the Open University's guidelines "Data Protection Policy"[14], the "Policy on Ethical use of Student Data for Learning Analytics"[15],the Data Protection Act UK (Gov.uk, 2017) and the EU General Data Protection Regulation (GDPR)[16].

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[10] https://www.bera.ac.uk/publication/ethical-guidelines-for-educational-research-2018
[11] https://www.bps.org.uk/psychologists/standards-and-guidelines
[12] https://www.jisc.ac.uk/guides/code-of-practice-for-learning-analytics
[13] https://www.open.ac.uk/research/sites/www.open.ac.uk.research/files/files/ecms/research-pr/web-content/Ethics-Principles-for-Research-involving-Human-Participants.pdf
[14] http://www.open.ac.uk/students/charter/sites/www.open.ac.uk.students.charter/files/files/ecms/web-content/data-protection.pdf
[15] http://www.open.ac.uk/students/charter/sites/www.open.ac.uk.students.charter/files/files/ecms/web-content/ethical-use-of-student-data-policy.pdf
[16] https://eugdpr.org/

Firstly, this research has been granted ethical approval from the Open University's Human Research Ethics Committee (HREC/2584/NGUYEN for Study 1, 3, 4; HREC/2693/NGUYEN for Study 2) (Appendix 1, Appendix 3). According to the Data Protection Policy[1] at the Open University, "*to support you in your studies. We may use information you have given us such as your ethnic background, disability and/or educational qualifications in addition to information we collect about your participation in learning activities to identify students who require additional support or specific services. We consider your disclosure of such information and your acceptance of the terms and conditions of registration as explicit consent to use this information for this purpose*." Therefore, all the students gave informed consent when they accept the terms and conditions of registration. Since all registered students at the OU have given their consent to the OU according to the Data Protection Policy, no further consensus from students were needed in this PhD project.

Secondly, the researcher has undergone various training in data protection with up-to-date guidelines and obtained a certificate of completion of GDPR training to ensure the ethical use of the data collected (Appendix 2). All personally identifiable information such as student names, student id, and email address were removed and anonymised before publishing. Module name and module code were also anonymised before publishing to protect the identity of the chosen modules. All interview responses were anonymised before sharing the transcripts with the supervisors. Data in this thesis are securely stored on OU protected servers. Only the primary researcher has access to the datasets.

With regards to Study 2 (interviews), all participants have given explicit consent by reading and signing the consent form as well as the participant information sheet before doing the interview (Appendix 3-6).

3.5 Conclusions

This chapter has provided explanations and justifications of the chosen measurements and methods to address the research questions in this thesis. The next four Chapters (4-7) will describe the methods of each study in more details and present the findings from each research question.

Chapter 4 - Study 1 How teachers design for learning[17]

As described in chapter 3, the empirical work for this thesis comprised of four separate studies. This chapter describes Study 1, which explores the temporal aspects of LD and interplay between learning activity types. Section 4.1 – Introduction summarises the rationale of the study and presents its research questions. Section 4.2 – Methods describes an overview of the specific methods used in Study 1, including information about the setting, participants, instruments and data analysis. Section 4.3 – Results presents the findings in relation to each research question. Section 4.4 – Discussion sets out the implications as well as the limitations of Study 1 and provides connections to the subsequent empirical work.

4.1 Introduction

Chapter 2 has highlighted the importance of LD representations in making existing LDs more visible. By doing so, researchers can gain a better understanding of how teachers design for learning and compare LDs across modules and disciplines (Dalziel et al., 2016; Maina et al., 2015). Although there have been many studies evaluating the use of LD tools (Hernández-Leo et al., 2018; Laurillard et al., 2018) and investigating teachers' LD process (Bennett et al., 2015; Bennett, Dawson, et al., 2017; Bennett et al., 2018), only a few studies have explored how LD representations can inform us about how teachers design their courses (Toetenel et al., 2016a, 2016b). One possible explanation for the lack of empirical studies on LD representations is that most existing LD tools have only been adopted by a relatively small number of practitioners, usually in an experimental setting designed for a research project. Therefore, it is difficult to synthesize and analyse LD data systematically. The OU is a notable exception because the OULDI project has been rolled out at scale across hundreds of modules since 2013 (Cross et al., 2012). As a result, a large number of LD representations have been generated and stored, providing a great opportunity to examine LD patterns across many modules.

For example, Toetenel et al. (2016a) analysed 157 LD representations at the OU and found that the majority of educators used two types of learning activity most widely, namely assimilative activities

[17] The empirical investigations undertaken for this chapter have now published as:

1. **Nguyen, Q.,** Rienties, B., & Toetenel, L. (2017). *Unravelling the dynamics of instructional practice: a longitudinal study on learning design and VLE activities*. In Proceedings of the 7th International Learning Analytics & Knowledge Conference, LAK 17, ACM, New York, NY, USA, pp. 168–177.
2. **Nguyen, Q**., Rienties, B., & Toetenel, L. (2017). Mixing and matching learning design and learning analytics **(best paper award).** In P. Zaphiris & A. Ioannou (Eds.), *Learning and Collaboration Technologies: Forth International Conference, LCT 2017, Part II, Held as Part of HCI International 2017, Proceedings* (Vol. 10296, pp. 1-15). Cham: Springer International Publishing.

(reading, watching, and listening) and assessment activities. On average, assimilative and assessment activities accounted for 39.27% and 21.50% of the total workload respectively ($SD_{assimilative}$=17.17, $SD_{assessment}$=14.58). These were not the only learning activities uncovered by this type of analysis as the researchers also discovered that 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) activities form part of the LD plan for these 157 modules.

Although the above study has shown an overview of how LDs were configured at the OU, the aggregated figures at module level omitted the dynamic temporal characteristics of LDs. As argued in chapter 2, learning is a dynamic temporal process occurring over time, so as LD. Teachers deliberately make unique and perhaps inconsistent decisions during the learning process depending on the specific learning goals of each study phase. Therefore, it is imperative to unpack how LDs were configured over time:

RQ1.1 What are the temporal characteristics of learning design?

Another research gap in the LD literature was the lack of studies exploring the interplay between different types of learning activity over time. Previous studies have shown that teachers used a mix of learning activities within a learning sequence or a task (AUTCLearningDesign, 2002; Bennett et al., 2015; Hora et al., 2013). For example, Hora et al. (2013) used network analysis to illustrate a diverse set of instructional practices between math, physics, biology and geology courses regarding how teachers mix and match various teaching methods and instructional technologies. If we only concentrate on a single component of LDs in isolation, we might omit the complexity and critical features of the instructional dynamics and interplay between activities. Therefore, the next RQ investigates how different types of learning activity interconnect within an LD.

RQ1.2 How do different types of learning activity interact with each other?

To address these two research questions, Study 1 carried out a combination of data visualisations, descriptive statistics, and network analysis based on LD data collected from 37 undergraduate modules over 30 weeks. The next section provides an in-depth overview of the methods employed in Study 1 to address these questions.

4.2 Methods

4.2.1 Setting and Participants

Study 1 took place at the OU with a focus on undergraduate modules because they accounted for the largest number of students and subsequently had the highest proportion of students dropping out (Nguyen, Thorne, et al., 2018; Rienties & Toetenel, 2016b). These modules have a strategic position within the OU curriculum and need to be designed well as students do not necessarily have the prerequisite qualifications required by other universities. This is because as its name suggests the OU is open to all. If students fail, then their future opportunities become limited and the mission of the OU is at risk.

Given the focus of the RQs on temporal characteristics of LDs, 56 modules were selected from the Activity Profile tool which mapped modules on a weekly basis (see section 4.2.2 below for a detailed description of the mapping process). After excluding 14 short and intensive training modules, because they did not count toward academic credit, Study 1 used only 42 modules. The next step was to filter out five postgraduate modules because these modules consisted of a small number of students, whose background is not comparable to most OU students. Therefore, Study 1 was conducted on 37 undergraduate modules.

Using descriptive statistics for these 37 modules, it is clear from Table 15 below that there was approximately an equal distribution of 30 to 60 credit modules investigated. With respect to the levels of study, level 1 modules accounted for the largest percentage (70.3%), followed by level 2 modules (13.5%), level 3 and access modules (8.1%). The sample was distributed across all the four faculties at the OU, with the highest frequency in STEM (35.1%), followed by Arts and Social Sciences (24.3%), Education, Health, and Languages (24.3%), and Business and Law (16.2%).

Table 15: Descriptive statistics of 37 modules

		Frequency	Per cent
Credits			
	30	17	45.9%
	60	20	54.1%
Level			
	0	3	8.1%
	1	26	70.3%
	2	5	13.5%
	3	3	8.1%
Faculty			
	Arts & Social Sciences	9	24.3%
	Business & Law	6	16.2%
	Education, Health, Languages	9	24.3%
	STEM	13	35.1%

Note: Level 1, 2, 3 at the OU are equivalent to introductory, intermediate, and advanced courses. Level 0 represents access modules

4.2.2 Instruments

Data for Study 1 was collected from the Activity Profile tool (Toetenel et al., 2016a; Whitelock et al., 2016) which was designed to help teachers map different types of learning activity across a course or sequence of learning events (see section 3.2.2). The tool was developed based on the OULDI's learning activity taxonomy which consists of seven types of learning activity: assimilative, productive, assessment, communication, finding and handling information, interactive, and experiential. A detailed discussion about this taxonomy can be found in chapter 2 and the measurement can be found in chapter 3.

To ensure the quality of data, two approaches were taken by the researcher. Firstly, throughout the process, I maintained continuous discussions with four learning designers in the Institute of Educational Technology, who were responsible for the mapping process of these modules. I also joined several internal meetings of the LD team to understand the module mapping protocols. Secondly, I carried out independent cross-checking with each selected module based on its online module guide available on the OU website (Figure 11).

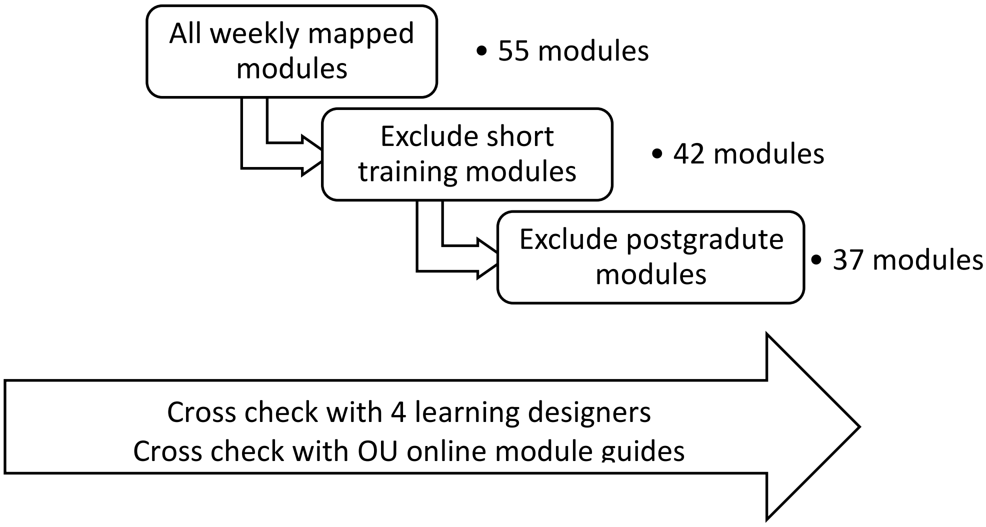


Figure 11. Sampling process

4.2.3 Data analysis

To address RQ1.1, a combination of data visualisation, descriptive statistics, and correlational analysis was used to explore the overall trends within the data. The data visualisation was completed using Tableau 10.1.6 and the descriptive statistics and correlational analysis were done using SPSS 23.

To answer RQ1.2, network analysis was used as this technique enables us to quantify and visualise the interactions and connections between the seven types of learning activity. A discussion about the background of network analysis can be found in chapter 3.

While the application of network analysis in education has primarily focused on modelling interactions between students, there has been very limited studies applying network analysis to model interactions between learning activities. To help readers understand the data analysis process, Table 16 showed an example of an LD mapping for 4 weeks. For example, in week 1, students were expected to spend 3.8 hours on readings, watching, listening activities and 0.8 hours on productive activities.

Table 16. Example of an LD mapping at a weekly level (unit=hours)

	Week 1	Week 2	Week 3	Week 4
Assimilative	3.8	4.3	2.8	1.3
Information				
Communication				
Productive	0.8	3.9	2.6	1.4
Experiential				0.5
Interactive				
Assessment			1.8	3

This LD mapping was a weighted two-mode network as it consisted of different learning activity types (mode 1) across several weeks (mode 2) as illustrated in Figure 12 below. Since I am primarily interested in the relationships among learning activity types, the dataset was transformed into a one-mode network in line with Hora et al. (2013). In doing so, two assumptions were made.

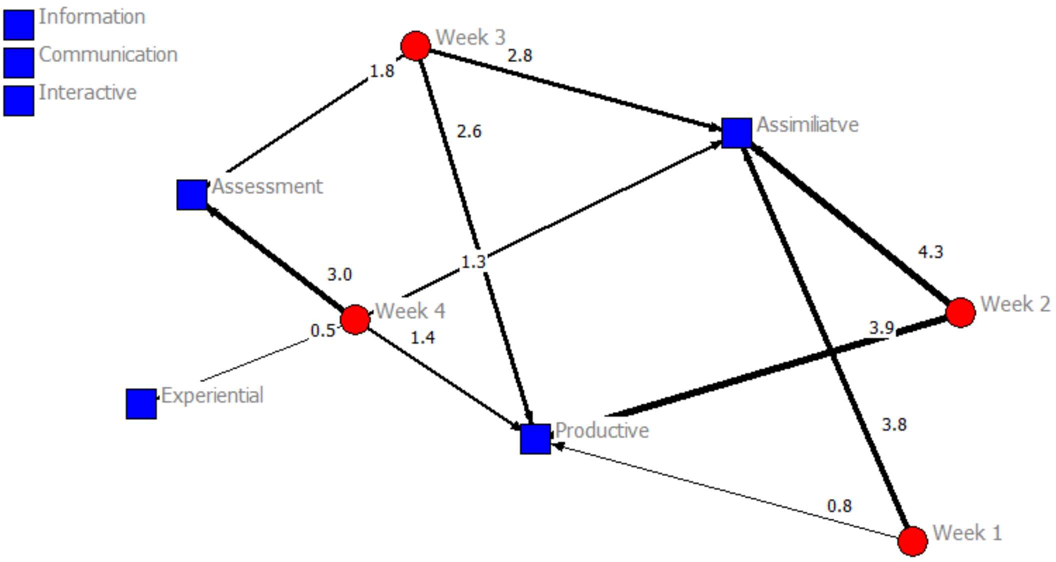


Figure 12. A weighted two-mode network of module X across the first five weeks

Firstly, two learning activities (blue nodes) become connected if they were present in the same week (red nodes). For example, if teachers allocated 3.8 hours for assimilative (e.g., readings) and 0.8 hours for productive activities in week 1, then assimilative and productive activities become connected (Figure 13).

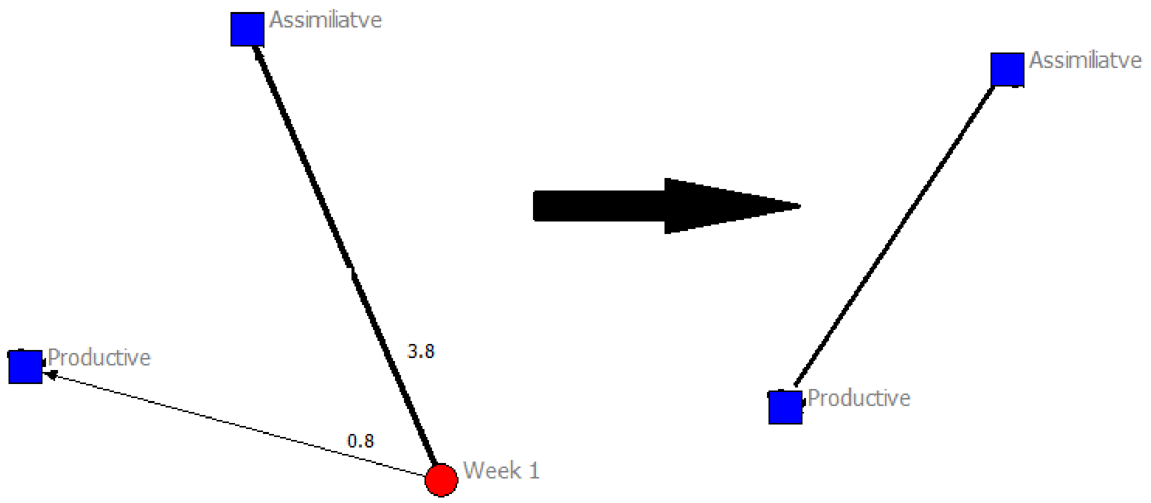


Figure 13. Transformation of a two-mode network into a one-mode network

However, simply visualising the connection between two activity types does not tell us much about the strength of the relationship. For example, module A with 5 hours of assimilative and 1 hour of productive activities will might look the same as module B with 1 hour of assimilative and 1 hour of productive. Since we captured how much time students were expected to spend on each LD each week, the weights of the two learning activities had directed towards identical weeks could also be measured. In this type of projected network, the weight of a tie from one LD to another was not necessarily equal to the weight of the reverse. For example, in Figure 13, if 3.8 hours were spent on assimilative activities and 0.8 were spent on assessment activities in the same week, then the weight from assimilative to assessment is recorded as 3.8 and the weight of the reverse is recorded as 0.8.

Second, the weight of each tie was discounted for the number of learning activity types in the same week (Newman, 2001). It can be argued that the tie between the two activity types becomes weaker when there are more activity types that are present in the same week. A simple analogy is the connection between two people is stronger there are fewer people in their group. 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.

After transforming the dataset from two-mode to one-mode network, I used the Netdraw function of UCINET 6.627 (Borgatti et al., 2002), which is based on non-metric multidimensional scaling (Kruskal, 1964), to visualise the co-occurrences between each pair of learning activities across all weeks. The stress value was computed in order to determine the number of dimensions. Since all the stress values of two-dimensional scaling were far below 0.2, the graphs were visualised in two-dimensional space (Everton, 2012). The nodes represent different learning activity types. The tie represents the co-occurrence of two learning activity types in the same week. The thickness of the line reflects the strength of the ties. In other words, the thicker the line, the higher the weights of the tie between two learning activity types.

In addition, descriptive network metrics were reported to support the reader's interpretation:

- *Network density*: The percentage of existing ties out of all possible ties. The higher the density, the more variety of combinations between activity types was used in an LD.
- *Out-degree centrality*: The frequency of an activity type was used with other types
- *In-degree centrality*: The frequency of other activity types was used with an activity type

To address RQ1.2, which examines how teachers combine different types of learning activity in their LD, the first part of network analysis assumed that two learning activity types were "connected" if they were present in the same study week. For example, if week 1's learning activities consist of assimilative activities (i.e. readings) and productive activities (i.e. open-ended questions), then assimilative and productive types are connected. The goal of RQ1.2 is to illustrate the diversity in how teachers mix and match different types of learning activity across modules. Due to limited space, I chose to report four exemplary modules from four different disciplines out of 37 modules to highlight different variations in LD.

While the first part of network analysis considers interactions between activity types at a weekly level, one could argue there are multiple learning tasks within a week. Thus, how teachers combined different activity types depends on the nature of each individual task. Therefore, the second part of network analysis was conducted at a learning task level. That means two activity types were connected only if they were used in the same learning task. For example, activity 1.1. consists of readings and finding information, then assimilative type and finding information type are connected. This fine-grained network analysis was carried out on 268 individual learning tasks on a level 1 Social Sciences module because this module has been mapped at a task level.

4.3 Results

There was a large variation in the size of modules ranging from 208 to 3707 enrolled students (M=1221.4, SD=964.93) as shown in Table 17. The average pass rate, which was calculated as the percentage of passed students amongst registered students, was 63.63% (SD=8.84%). On average, 69.10% of the registered students completed the module (SD=6.82%), which means 31.90% of them either dropped out or did not engage with the final assessment. However, 91.81% of those who completed the module and took part in the final assessment achieved a passing score. These patterns suggested that perhaps assessments were not the main reason behind a low retention rate. However, keeping the students engaged throughout 31 weeks long of studying was the main challenge.

Table 17. Descriptive statistics of selected modules starting 2014J

Variables	N	Minimum	Maximum	Mean	Std. Dev
Registrations	37	208	3707	1221.4	964.93
Completions	37	163	2461	832.3	660.55
Passed	37	149	2347	766.8	623.24
Completed of registered	37	56.49%	85.08%	69.10%	6.82%
Passed of completed	37	77.48%	98.57%	91.81%	5.70%
Passed of registered	37	44.71%	81.78%	63.63%	8.84%

In line with previous findings (Rienties & Toetenel, 2016b; Toetenel et al., 2016a), assimilative, assessment, and productive activities were the predominant types of learning activity (Table 18). Assimilative activities accounted for half of the workload on average (M=50.0%, SD = 13.03%), followed by assessment (M=24.4%, SD=8.38%) and productive (M=17.6%, SD=12.39%). There was a large variation in terms of the total workload across modules. All modules have some proportions of assimilative, productive, and assessment but some modules did not have any communication, finding information, interactive, or experiential activities (Table 18).

Table 18. Descriptive statistics of seven types of learning activity in 37 modules

	N	Minimum	Maximum	Mean	Std. Deviation
Assimilative	37	23%	75%	50.0%	13.03%
Information	37	0%	8%	2.2%	1.98%
Communication	37	0%	9%	2.5%	2.96%
Productive	37	2%	59%	17.6%	12.39%
Experiential	37	0%	12%	1.1%	2.25%
Interactive	37	0%	19%	2.2%	4.56%
Assessment	37	13%	57%	24.4%	8.38%

Metric = % of total workload

A visual comparison of LDs across the four disciplines suggested that STEM modules were more likely to use experiential and interactive activities than other disciplines (Figure 14). Modules in Education, Health, and Languages had the highest proportion of workload for productive activities. A Kruskal-Wallis test indicated that the differences between disciplines in productive (X^2=14.37, p=0.002) and experiential activities (X^2=8.64, p=0.034) were statistically significant at 5% alpha (Table 19).

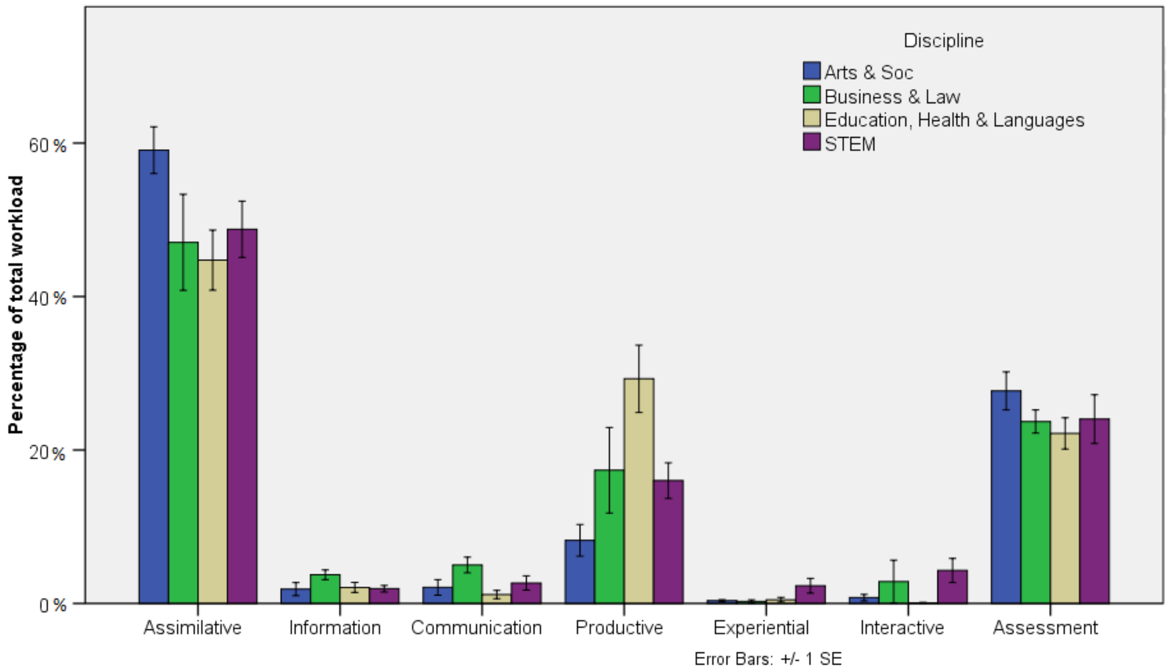


Figure 14. A comparison of seven learning activity types across four disciplines

Table 19. A Kruskal Wallis test comparing LDs between four disciplines

	Chi-Square	df	p-value
Assimilative	6.611	3	0.085
Information	5.762	3	0.124
Communication	7.075	3	0.070
Productive	14.37	3	0.002
Experiential	8.642	3	0.034
Interactive	7.405	3	0.060
Assessment	4.425	3	0.219

Kruskal Wallis Test

Grouping Variable: Discipline

These results based on aggregated figures of LD confirmed findings from previous studies (Rienties & Toetenel, 2016b; Toetenel et al., 2016a). It also added new insights into the disciplinary differences in LDs. The next section will unpack the changes in LDs over time.

4.3.1 RQ 1.1 Learning design over time

Figure 15 visualised the changes in total workload of 37 modules over 31 weeks grouped by the number of credits. By default, the total workload of 30 credit modules was lower than 60 credit modules. However, there were a lot of fluctuations in workload across modules over time ($M_{30\ credit}$ = 6.5, $SD_{30\ credit}$ = 3.11; $M_{60\ credit}$ = 8.9, $SD_{60\ credit}$ = 4.42) with a slight decrease in the last 4 weeks toward the end of the module (Table 20).

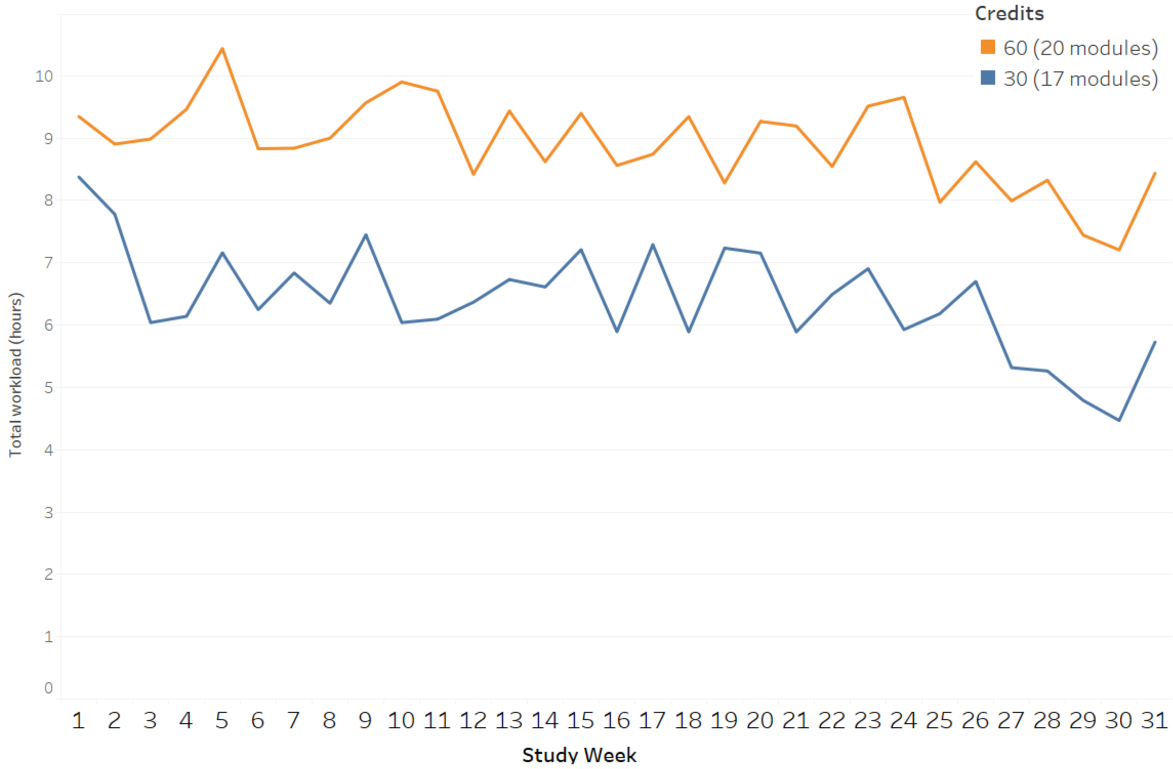


Figure 15. Visualisation of total workload over time of 37 modules over 31 weeks

Table 20. Descriptive statistics of seven learning activity types of 37 modules over 31 weeks

	N	Min	Max	Mean	Std. Deviation
30 credits modules					
Assimilative	475	0.0	12.4	3.1	2.36
Information	475	0.0	2.3	0.1	0.31
Communication	475	0.0	2.5	0.2	0.38
Productive	475	0.0	9.5	1.3	1.39
Experiential	475	0.0	9.0	0.1	0.71
Interactive	475	0.0	4.4	0.2	0.78
Assessment	475	0.0	10.5	1.3	2.23
Total	475	0.0	23.6	6.4	3.11
60 credits modules					
Assimilative	613	0.0	15.0	4.5	3.88
Information	613	0.0	13.0	0.3	0.92
Communication	613	0.0	11.0	0.3	0.89
Productive	613	0.0	12.5	1.3	1.94
Experiential	613	0.0	1.8	0.0	0.17
Interactive	613	0.0	19.1	0.1	0.87
Assessment	613	0.0	20.0	2.4	4.06
Total	613	0.0	35.9	8.9	4.42

Metrics = Hours

N = Number of data points per module per week. For example, a 30-week long module has 30 data points.

Figure 16 illustrates the average time students were expected to spend per module (in hours) on different learning activities over 34 weeks. Each colour represents a type of learning activities. The visualisation also confirmed the dominance of assimilative (orange), assessment (blue), and productive (purple) learning activity types. Assimilative activities were present throughout most of the learning process except for the last four weeks and accounted for half of the total workload (M=3.9, SD=3.37).

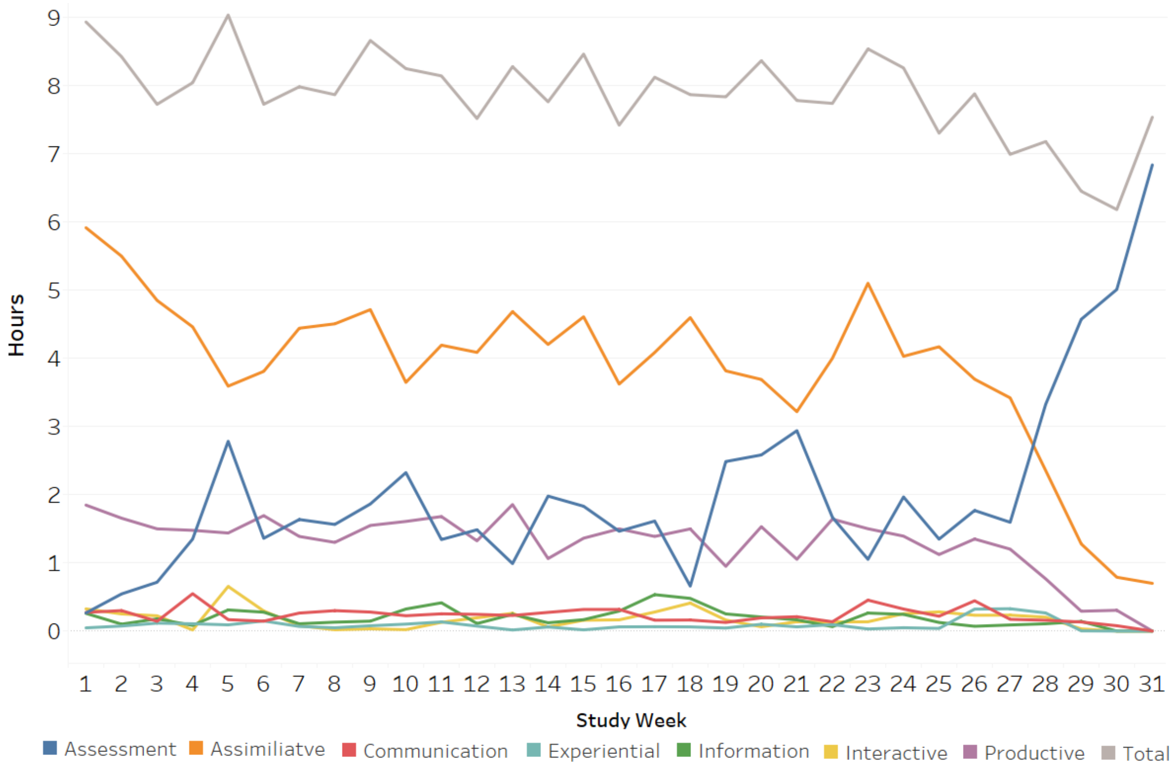


Figure 16. Visualisation of seven learning activity types over time of 37 modules over 31 weeks

Interestingly, there was an opposite trend between assimilative and assessment activities throughout the course (Pearson's r = -0.462, p <0.01). More assimilative activities were used at the beginning of a module, whereas more assessments were used toward the end. Assessment activities were also negatively correlated with other types of learning activity (Table 21). In other words, teachers deliberately reduce the workload of other learning activity types when an assessment was activated.

Table 21. Correlation analysis of seven learning activity types over time of 37 modules

	1	2	3	4	5	6	7	8
1. Assimilative	1							
2. Information	.082**	1						
3. Communication	.166**	.167**	1					
4. Productive	.161**	.167**	.130**	1				
5. Experiential	.021	-.021	-.022	-.002	1			
6. Interactive	.016	.015	.050	.008	.012	1		
7. Assessment	-.462**	-.115**	-.124**	-.292**	-.062*	-.003	1	
8. Total	.555**	.248**	.300**	.362**	.078**	.230**	.283**	1

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

N=1088 data points

After capturing the dynamic picture of LD over time, I took a further step to investigate how LDs were configured across different modules. I reported four exemplary modules across four disciplines with a variety of configurations and patterns of learning activities (Figure 17). In line with the findings above, all four modules extensively made use of assimilative (orange), productive (purple), and assessment activities (blue). However, there are subtle differences in the way each module utilised these three activity types.

The first module in Arts followed a traditional design, with a lot of reading, watching, listening activities. Its assessment consisted of 5 continuous assessments, so-called Tutor Marked Assessments (TMAs) every 4-5 weeks and an end of module assessment (EMA) in week 30. The workload of this module was relatively constant for most parts, except for the peak in week 8 which had a double workload (i.e., 11.31 hours) compared to other weeks.

The second module in Health was similar to the first module in Arts. However, the former used more productive activities and had a two-week long studying time for each TMA. The third module in Science adopted a continuous assessment strategy using a lot of quizzes throughout the learning process. This module also had a considerable amount of interactive (yellow) and experiential (light blue) activities compared to other modules. There were several dips in workload in week 14, 19, and 25 which represented TMA preparation weeks. The dip in week 29 represented an EMA preparation week. The fourth module in languages had a higher mix of assimilative and productive activities. There was also a higher presence of communication activities (red) in this module.

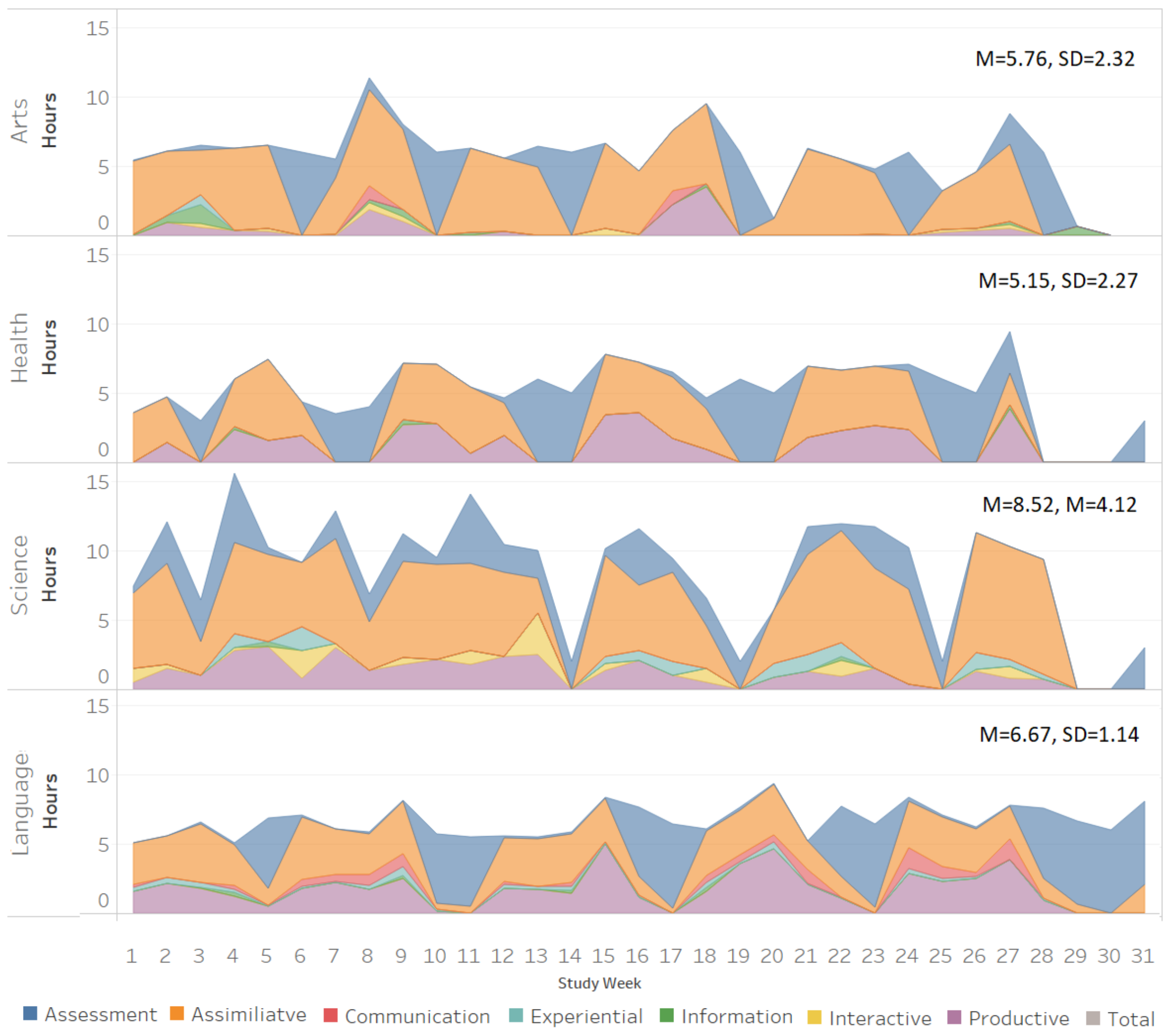
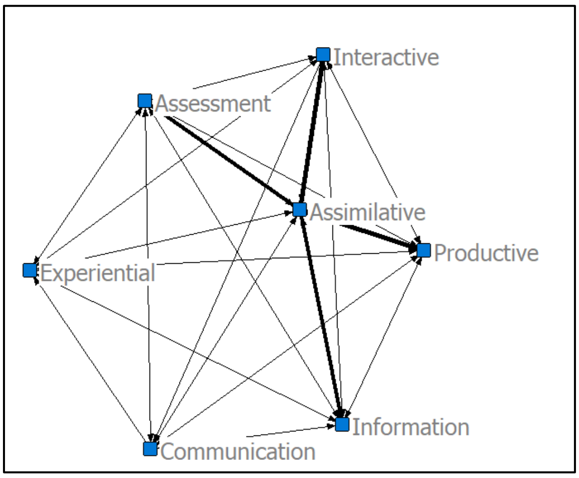


Figure 17. Four exemplary modules from Arts, Health, Science, and Languages

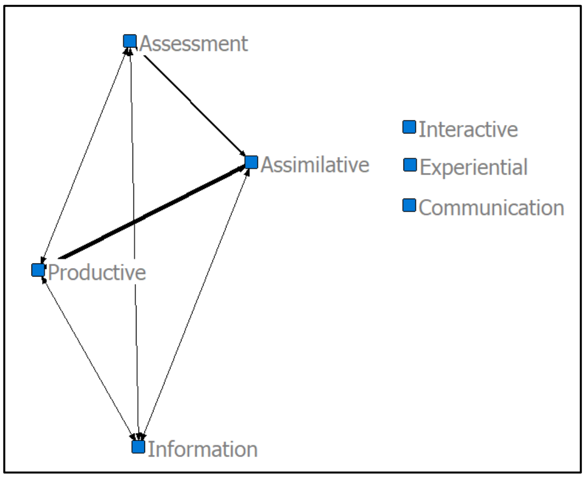
In summary, the findings have started to demonstrate through visualisations and statistical analysis the overall trends in LDs across 37 modules over 31 weeks. The three main types of learning activity namely assimilative, productive, and assessment were visible in all modules. There was a moderate negative correlation between assimilative and assessment activities. A closer look into each module individually revealed subtle differences in how each teacher utilised each learning activity type. The next section will explore further the interplay between the different types of learning activity using network analysis.

4.3.2 RQ 1.2 Interplay between learning activities

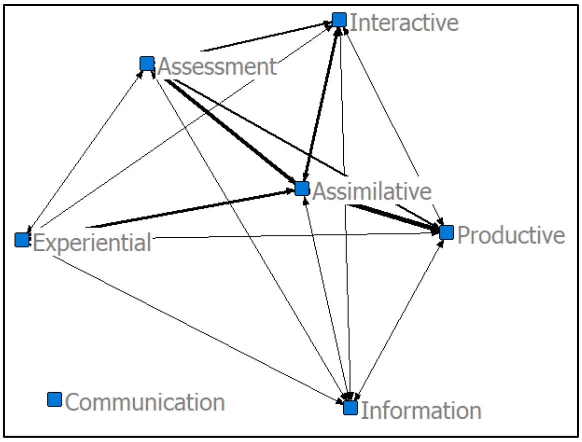
Figure 18 visualises networks of learning activities in the same four exemplary modules in RQ1.1. To recap, two nodes (i.e., activity types) are assumed to be connected if they were used in the same study week. The thickness of each tie represents the strength of the connection between two activity types. The thicker the line is, the stronger the relationship between two nodes. Network density represents the percentage of the existed ties out of the maximum possible ties. In simple terms, the higher the network density is, the more variety of learning activity types were used.



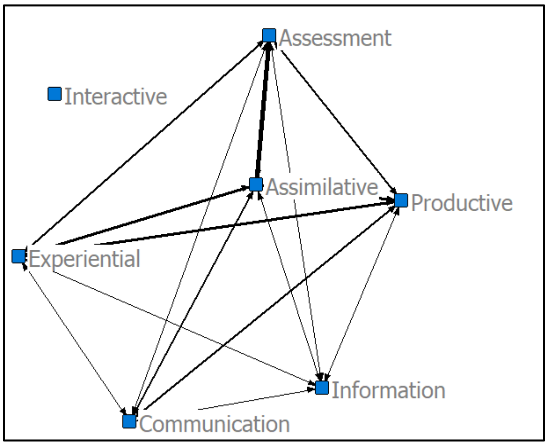
Module 1, Arts (density = 1)



Module 2, Health (density = 0.286)



Module 3, Science (density = 0.714)



Module 4, Languages (density = 0.714)

Figure 18. Network visualisations of four exemplary modules

Note: The weight of ties was omitted for the sake of visual clarity. Instead, I reported the centrality measures in Table 22 below.

Table 22. Freeman's centrality measures of seven learning activity types

	Arts		Health		Science		Languages	
	Out degree	In degree	Out degree	In degree	Out degree	In degree	Out degree	In degree
Assimilative	101.6	11.9	65.9	31.7	152.0	36.9	75.2	56.9
Information	3.3	23.4	0.9	9.3	0.6	8.7	0.9	6.5
Communication	2.5	5.3	0.0	0.0	0.0	0.0	10.4	24.0
Productive	12.1	33.0	37.8	56.1	36.9	78.0	52.1	32.9
Experiential	0.7	1.8	0.0	0.0	10.3	32.5	5.5	46.0
Interactive	2.8	29.7	0.0	0.0	11.9	39.9	0.0	0.0
Assessment	7.1	25.0	5.0	12.6	43.5	59.0	56.6	34.3

Additional network centrality metrics (out-degree and in-degree) were reported to support the reader's interpretation (Table 22). Out-degree in an unweighted network refers to the number of ties directed outwards (or inwards for in-degree). However, for a weighted network, out-degree refers to the sum of weights directed outwards (or inwards for in-degree) (Newman, 2001). For example, assimilative activities in the Arts module had out-degree = 101.6 and in-degree = 11.9. In other words, there were in total 101.6 hours of assimilative activities that were mixed with other types. The total number of hours of other learning activity types which were used in combination with assimilative activities was 11.9 hours.

In Module 1 in Arts, there were strong connections between assimilative and assessment, assimilative and production, assimilative and interactive, and assimilative and information. There were weak links among other learning activity types. The network density was 100% which suggested that all seven types of learning activity were used in the module.

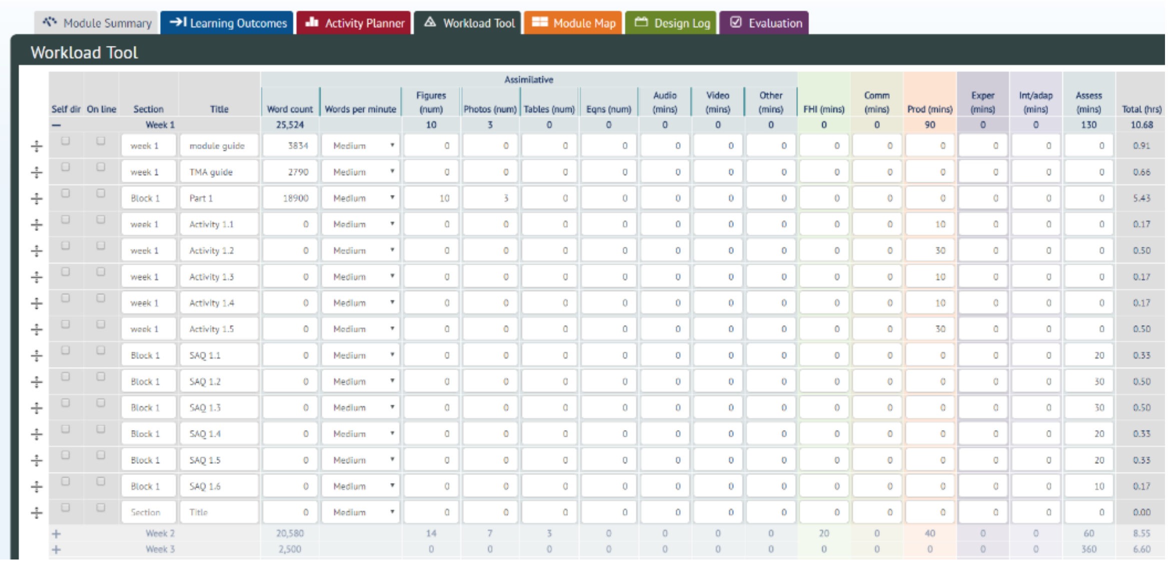
In Module 2 in Health, there was a strong link between assimilative and productive activities. However, this module did not use any interactive, experiential, or communication activities. The network density was low (28.6%) which suggested that there was a lack of variety in the LD. The most common repertoire of practice was assimilative and productive (10 out of 31 weeks)

In Module 3 in Science, there were strong links between assimilative and assessment, assimilative and production, assimilative and interactive, and assimilative and experiential. There were no communication activities in this module (e.g., discussing module related content with peers or tutors in online disucsison forums). The network density was 71.4% suggesting a good mix of learning activities was used. The most common repertoire of practice was assimilative, productive, interactive, and assessment (7 out of 31 weeks), and assimilative, productive, and assessment (6 out of 31 weeks).

In Module 4 in Languages, assimilative and experiential activities were often mixed with assessment and productive types. There were no interactive activities in this module. The most common repertoire of practice was assimilative, communication, productive, experiential, and assessment (9 out of 31 weeks) followed by assimilative, productive, experiential, and assessment (7 out of 31 weeks).

To sum up, the network analysis has uncovered complex LD strategies used in four different modules, which were not visible with simple line graphs. The analysis indicated a strong influence of assimilative activities in workload and in relations with other learning activities. In the next step, I will further explore the media types that are used in assimilative activities, which provides a rich picture of the media mix used in a particular LD. This is important because not only which learning activity type was used but also how it was delivered will have different effects on student learning.

This analysis was carried out on 268 learning tasks of a selected module in Social Sciences because it was one of the few modules that have been mapped at a task level (Figure 19).


Module Summary | Learning Outcomes | Activity Planner | Workload Tool | Module Map | Design Log | Evaluation

Workload Tool

Self dir	On line	Section	Title	Word count	Words per minute	Figures (num)	Photos (num)	Tables (num)	Eqns (num)	Audio (mins)	Video (mins)	Other (mins)	FHI (mins)	Comm (mins)	Prod (mins)	Exper (mins)	Int/adap (mins)	Assess (mins)	Total (hrs)
						Assimilative													
–		Week 1		25,524		10	3	0	0	0	0	0	0	0	90	0	0	130	10.68
		week 1	module guide	3834	Medium	0	0	0	0	0	0	0	0	0	0	0	0	0	0.91
		week 1	TMA guide	2790	Medium	0	0	0	0	0	0	0	0	0	0	0	0	0	0.66
		Block 1	Part 1	18900	Medium	10	3	0	0	0	0	0	0	0	0	0	0	0	5.43
		week 1	Activity 1.1	0	Medium	0	0	0	0	0	0	0	0	0	10	0	0	0	0.17
		week 1	Activity 1.2	0	Medium	0	0	0	0	0	0	0	0	0	30	0	0	0	0.50
		week 1	Activity 1.3	0	Medium	0	0	0	0	0	0	0	0	0	10	0	0	0	0.17
		week 1	Activity 1.4	0	Medium	0	0	0	0	0	0	0	0	0	10	0	0	0	0.17
		week 1	Activity 1.5	0	Medium	0	0	0	0	0	0	0	0	0	30	0	0	0	0.50
		Block 1	SAQ 1.1	0	Medium	0	0	0	0	0	0	0	0	0	0	0	0	20	0.33
		Block 1	SAQ 1.2	0	Medium	0	0	0	0	0	0	0	0	0	0	0	0	30	0.50
		Block 1	SAQ 1.3	0	Medium	0	0	0	0	0	0	0	0	0	0	0	0	30	0.50
		Block 1	SAQ 1.4	0	Medium	0	0	0	0	0	0	0	0	0	0	0	0	20	0.33
		Block 1	SAQ 1.5	0	Medium	0	0	0	0	0	0	0	0	0	0	0	0	20	0.33
		Block 1	SAQ 1.6	0	Medium	0	0	0	0	0	0	0	0	0	0	0	0	10	0.17
		Section	Title	0	Medium	0	0	0	0	0	0	0	0	0	0	0	0	0	0.00
+		Week 2		20,580		14	7	3	0	0	0	0	20	0	40	0	0	60	8.55
+		Week 3		2,500		0	0	0	0	0	0	0	0	0	0	0	0	360	6.60

Figure 19. LD mapping at a task level of an exemplar module in the Social sciences

When coding learning activities, media assets are indicated at a high level, in order to compare the overall amount of time spent on video, words, photos, and figures for instance. This high-level notation does not indicate whether a module includes one video of half an hour or six videos of five minutes, as the total time spent per item is recorded. The decomposition of assimilative activities of the exemplary module is illustrated in Figure 20. On average, most assimilative activities took forms of words (M= 3.32, SD=1.92). This suggests that educators were more likely to use reading materials to convey information, but most weeks also included another media element. Figure 20 also shows that figures and videos were also used over time, but in less frequency compared to words.

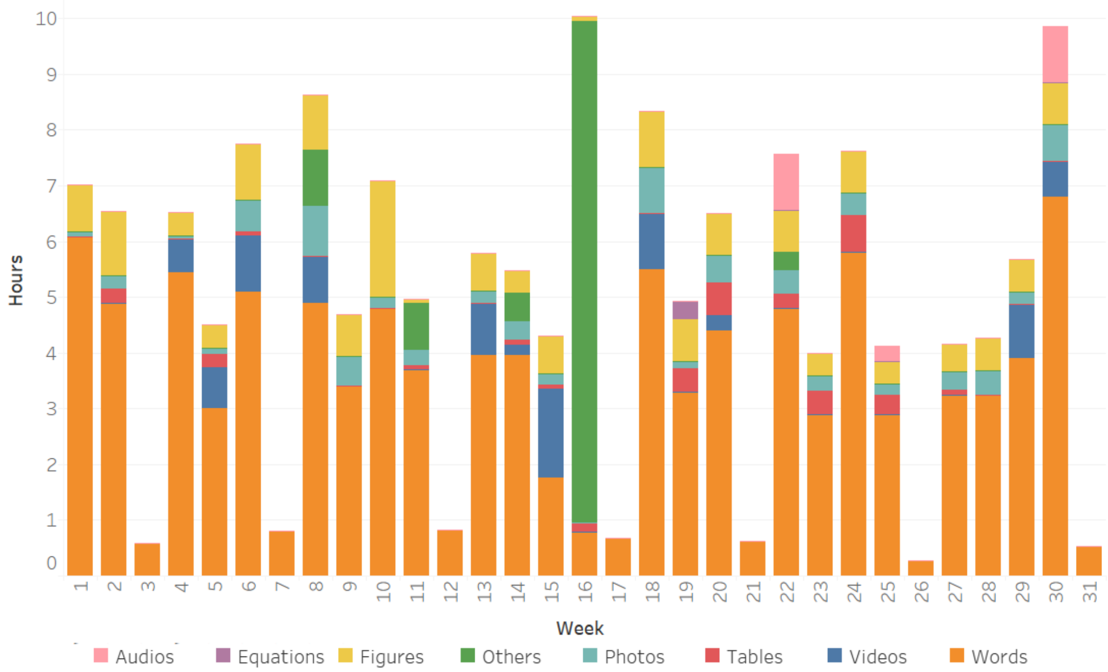


Figure 20. Assimilative activities of an exemplar module in Social sciences

Using descriptive statistics, Table 23 indicated that on average, teachers in this module allocated 0.98 hours for each learning task (SD=1.75). Assimilative activities accounted for more than half of the workload of each learning task (M=0.58, SD=1.60). Readings were the main component of assimilative activities accounting for 0.39 hours (24.3 minutes) on average.

Table 23. Descriptive statistics of 267 learning tasks in an example module in Social Science

Variable	N	Mean	SD	Min	Max
Assimilative	267	0.58	1.60	0	9.00
Words	267	0.39	1.17	0	6.80
Figures	267	0.06	0.23	0	2.08
Photos	267	0.03	0.12	0	0.90
Tables	267	0.01	0.07	0	0.58
Equations	267	0.00	0.02	0	0.33
Audios	267	0.01	0.09	0	1.00
Videos	267	0.03	0.12	0	1.00
Others	267	0.04	0.56	0	9.00
Information	267	0.06	0.24	0	2.00
Productive	267	0.09	0.18	0	1.00
Experiential	267	0.00	0.00	0	0.00
Assessment	267	0.25	0.91	0	6.00
Total	267	0.98	1.75	0	9.00

Note: Metric = hours.

Further SNA analysis demonstrated the inter-relationships between different types of assimilative activities and other learning activities (Figure 21). There were in total 40 ties in the network, with a density of 22% and the average distance between a pair of ties of 2.036. Firstly, there were strong connections between the use of words with photos, tables, and figures. These forms of assimilative activities often appeared together in reading materials. In line with the multi-media principle of Mayer (2002), this module employed an integrated representation of graphics and words. Given the nature of this module, most of the graphics were representational (visuals that illustrate the appearance of an object), organizational (visuals that show qualitative relationships among content), and interpretive (visuals that make intangible phenomena visible and concrete) (Mayer, 2002). The use of words had a strong influence on photos, figures, and tables with a weight of 38.9, 16.4, 38.4 respectively (out-degree centrality = 118.541).

Secondly, videos were often used in combination with finding information activities and productive activities. For example, students were asked to watch a short video, and answer some questions using the information from the video. Alternatively, students were asked to interpret and draw a conclusion using the information from the video.

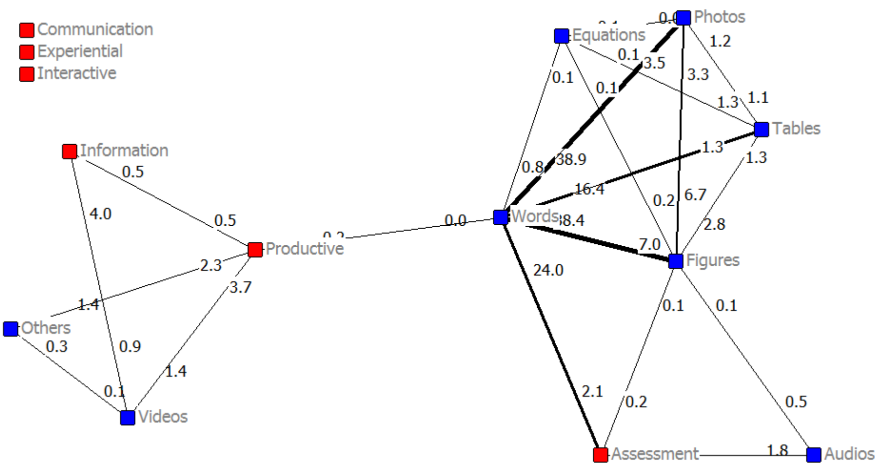


Figure 21. Inter-relationships between assimilative activities and other activities of an exemplar module in Social sciences

Note: Blue nodes represent assimilative activities, red nodes represent other activities

The structure of the network also revealed interesting findings. There were two local networks in which the first one (right-hand side) consists of mainly assimilative activities, whereas the second one (left-hand side) consisted of some assimilative activities (i.e., videos, others), finding information and productive activities. The connection between words and productive activities acted as a bridge between these two local networks. The betweenness centrality of the edge productive and words was 28, which means there were 28 flows between all pairs of nodes which were carried using this edge.

4.4 Study 1 Discussion

Research question 1.1 of Study 1 explored how LDs were configured over time by identifying common LD patterns amongst 37 modules as well as varieties of LD across different modules and disciplines. The findings were consistent with previous studies at the OU (Rienties & Toetenel, 2016b; Toetenel et al., 2016a), which confirmed the dominance of assimilative activities followed by assessment and productive activities in most modules. Furthermore, Study 1 has shed new light on how LDs changed throughout their module's timeline. The findings demonstrated that the total workload fluctuated from week to week, with a standard deviation of 3.11 hours for 30 credit modules (M=6.5) and 4.42 hours for 60 credit modules (M=8.9). This was equivalent to approximately 50% variation in weekly workload across modules. At the beginning of the module more assimilative activities were introduced, while towards the end more assessment activities were used, and the overall workload decreased. There was a negative correlation between assessment and all other activities, suggesting that teachers reduced studying workload on purpose when they introduced assessment activities.

While the fluctuations in workload across modules could be explained by the differences in subject content, these fluctuations still remained within the module itself, as illustrated by the four exemplary modules. Keeping a balance and consistent workload is crucial to the success of OU students. For example, a full-time OU student needs to complete 120 credits worth of study (i.e., two 60 credit modules). If the workload between and within these two modules varied by 50% from week to week, then a student is likely to feel overwhelmed and may struggle to allocate sufficient time for studying (Kyndt et al., 2014; Whitelock, Thorpe, et al., 2015). For a part-time OU student, these fluctuations in workload have even more severe consequences to their performance because of their studying time is limited by other duties such as full-time job, part-time job, or family (Nguyen, Thorne, et al., 2018). By making instructional practices more visible through LD representations, teachers and curriculum managers can identify trends and issues in their designs. Most importantly, the visualisations can help teachers narrow down the potentially problematic area in their LD (e.g., the workload increased by 100% in week 8). By doing so, teachers can focus their time and effort on important issues within their LD.

A second important finding from Study 1 was the under-representation of collaborative and interactive/experiential activities in all modules. It has been established in educational literature that collaboration and interactive activities have a positive impact on student engagement and academic performance (Cherney et al., 2017; Kreijns et al., 2003). Learning to effectively collaborate in digital environments is a valuable skill in the 21st century. However, designing collaborative activities in an online learning environment can be challenging for several reasons (Thorpe, 2002). For example, the lack of face to face interactions makes it difficult to establish trust and rapport between students in an online setting (Kreijns et al., 2003; Thorpe, 2002). The diversity in OU student population in terms of age and prior educational background can also be a barrier for collaboration (Kreijns et al., 2003; Thorpe, 2002). There are also practical and logistic challenges in organising collaboration activities at scale for a large number of students, such as assessment strategy for collaboration, and staff resources.

Research question 1.2 of Study 1 examined the interplay between different types of learning activity. Through a novel application of network analysis, the findings illustrated the underlying complexities in how teachers mix and match different activity types in their LDs. Even though all modules put a strong emphasis on assimilative activities type, each module utilised it with other learning activities in different ways. For example, the repertoire of practice in module 2 in Health (assimilative, productive) was different from module 3 in Science (assimilative, productive, interactive, and assessment), and module 4 in Languages (assimilative, communication, productive, experiential, and assessment). This is important for teacher reflection because two modules can have the same amount of activities, but how they were combined and used together can have different effects on student learning.

Further analysis of 268 individual learning activities in our social science module demonstrated the usage and connections of media in assimilative activities. Overall, most assimilative activities took forms of words. This suggests that educators were more likely to use reading materials to convey information, but also included another media element. The findings revealed strong ties between words, figures, photos, and tables. This implies that educators employed integrated representations of words and graphics, which has been shown to be effective in helping students absorb information (Mayer, 2002).

4.5 Conclusion

In conclusion, Study 1 investigated how LDs are configured over time by analysing 37 modules over 31 weeks at the Open University UK. By visualizing how LD varied week-by-week throughout the course, teachers can explicitly reflect on their practice as well as compare and contrast with others. Using network analysis, Study 1 illustrated how different learning activities interact with each other and which repertoire of practice was frequently adopted. The results indicated a wide variance in the number of learning activities was used as well as the workload balance across modules. The findings also highlighted the fluctuations in workload between and within modules, which could have important implications to OU students.

Study 1 has provided large-scale empirical evidence exploring two important and under-explored dimensions of LDs, namely time and network. Future research should continue investigating the temporal changes in LD such as how LD changes across a series of modules within a qualification, how LD changes from level 1 to level 2 and level 3, or how LD of the same module changes across different semesters. Similarly, interesting questions could be asked about the network structure of LDs such as how does a network of learning activities within a module interact with a network of students, what are the common LD patterns amongst multiple networks of learning activities (Holmes et al., 2019), or how does a network of learning activities change over time.

While Study 1 has described the overall LD patterns across 37 undergraduate modules from a number of disciplines, a limitation of Study 1 was the potential sampling bias in selecting modules due to the availability of the data. The findings were based on modules produced in 2014, which might not apply to new modules that were developed recently. Last but not least, Study 1 has not addressed the *why* question to provide an explanation for why teachers designed their module this way. To answer this, Study 2 will take a qualitative approach through 12 semi-structured interviews with module chairs to explain the underlying perspectives of teachers in designing their modules. Furthermore, Study 1 did not specifically focus on how the LD influenced actual student behaviour, which will be the focus of Study 3 and Study 4.

Chapter 5 - Study 2 The underlying factors behind teachers' design decisions

This chapter describes Study 2 in this thesis, which explores the underlying factors that influence how teachers design for learning in a distance learning setting through a series of qualitative interviews. Section 5.1 – Introduction summarises the rationale of the study and presents its research questions. Section 5.2 – Methods describes an overview of the specific methods used in Study 2, including information about the setting, participants, procedure, instruments and the data analysis techniques employed. Section 5.3 – Results presents the findings in relation to each research question. Section 5.4 – Discussion reports the implications as well as limitations of Study 2 and provides connections to Studies 3 and 4.

5.1 Introduction

In chapter 4, Study 1 has highlighted the overall trends as well as the differences between the ways in which teachers have designed their modules at the OU over a long period of time. In particular, the predominant learning activity types in most modules were assimilative, productive, and assessment activities, whereas interactive and communication activities, were used less in comparison. Furthermore, another important finding was the large variation in the estimated workload by teachers over time both within and between modules. However, these quantitative findings only provided one perspective on LD (i.e., *what* teachers have designed), while follow-up qualitative research is needed for an in-depth understanding of the observed phenomena (i.e., *how* teachers designed and *why* teachers designed the way they did). A mixed-method research design can help researchers triangulate the findings to increase the rigour and completeness of their findings (Creswell & Clark, 2017; Johnson et al., 2004) while they engage in a complex inquiry such as understanding LD. Therefore, this chapter reports an in-depth qualitative analysis of teacher reflections on the LD process at the OU over 2018-2019.

Extensive research in the field of LD has shown that LD is a multifaceted process which involves multiple stakeholders and different elements interacting in the process of designing and implementing teaching and learning activities (Bennett et al., 2015; Bennett, Agostinho, et al., 2017; Bennett, Dawson, et al., 2017; Conole, 2009; Lockyer et al., 2008). Dalziel et al. (2016) suggested that the LD process is driven by factors such as educational philosophy, educational theories and methodologies, and characteristics about learning environments. Firstly, the teacher's philosophy of how learning occurs will determine the instructional tasks accordingly. For example, behaviourists propose that learning happens through a stimulus-response process (Watson, 1913). This paradigm is often used in physical education and military training, in which LD consists of trials and repetitions (Light, 2008). In contrast, social constructivists often advocate for learning through collaboration as the development of knowledge is social situated and constructed through interactions with others (Laurillard, 2002; Vygotsky, 1980).

Secondly, LD decisions are also driven by the learning theories that teachers adopt. For example, a cognitive load theory (CLT) proposes that human working memory can only process a limited amount of information at a time (Kirschner, 2002; Paas et al., 2003; Sweller et al., 1998). CLT suggests that if the cognitive load exceeds our processing capacity, students will struggle to complete the activity successfully. CLT identifies three forms of cognitive load: intrinsic – related to the difficulty of the materials itself, extraneous – cognitive load generated by the way information was presented, and germane – cognitive load produced by the construction of schemas (Paas et al., 2003). By adopting this theory, teachers would often simplify their instructions or break a complex process into smaller chunks to reduce student's cognitive load.

Thirdly, LD decisions are often influenced by the characteristics of learning environments (Bennett et al., 2015). Examples include student demographics and prior knowledge, institutional policies, and technological infrastructure. As shown in Nguyen, Thorne, et al. (2018), OU students varied considerably in age, with 24% under 25 years old, 37% aged 26–35, 22% aged 36–45, 13% aged 45–55, and 5% aged 56 and over. More than half of them were working full-time (53%), while 21% were working part-time, 7% were looking after the home/family, and 5% were unemployed and looking for a job. Regarding students' qualifications, there are no formal academic entry requirements at an undergraduate level at the OU. In the study, 40% of the students had A levels or equivalent, 28% had less than A levels, 24% had higher education degrees, and 3% had a postgraduate qualification. On average, 10% of the students had a reported disability. This diverse population of students poses a great challenge for teachers in designing their modules.

As can be seen from Study 1, there were both common patterns and varieties in how different modules were designed at the OU. Given the complexity of LD based on the existing literature, and the empirical evidence from Study 1, the first RQ of Study 2 will explore underlying factors that influence teachers design decisions:

- **RQ2.1** What are the driving factors behind teachers' design decisions?

The Open University has been one of the pioneers in LD research for the last 10 years (Conole et al., 2004; Rienties et al., 2017). The OU offers a wide range of workshops and online visualisation tools to support and guide teachers in the design process (Toetenel et al., 2016b). As indicated previously, new modules at the OU are expected to join the LD workshops. A number of studies at the OU has made use of the LD data to explore trends and patterns of LD (Toetenel et al., 2016a, 2016b), and link LD with student behaviour, performance, and satisfaction (Rienties & Toetenel, 2016a, 2016b; Rienties et al., 2015). While the previous studies have reported a positive impact of OULDI on the teacher design process based on the LD data collected (Clifton, 2017; Toetenel et al., 2016a), limited attention has been paid to the affordances and barriers for teachers when they engaged in the OULDI process. This is important for two reasons.

Firstly, there has been a host of LD projects and tools developed by researchers around the world (AUTCLearningDesign, 2002; Dalziel, 2003; Koper et al., 2004; Laurillard et al., 2018). Although a lot of papers reported positive evaluations from users (Clifton, 2017; Hernández-Leo et al., 2018; Laurillard et al., 2018), it is still unclear why most of these LD tools have not been adopted by teachers as a part of their standard practices. Secondly, the OULDI is one of a few LD tools that has been rolled out across multiple institutions and structurally embedded as a part of the design protocols at the OU. Nonetheless, there seemed to be mixed feelings about the OULDI approach from OU staff when presenting my research to internal quality enhancement seminars and conferences. Therefore, an objective evaluation of the opportunities and challenges of implementing an LD tool on a large scale will help OU practitioners reflect on their approaches and may provide useful lessons for other institutions that seek to implement their own LD tools. Therefore, the second RQ of Study 2 is:

- **RQ2.2** What are the barriers and affordances of learning design adoption at the OU?

Finally, an important element in every design process is feedback and evaluation (Dalziel et al., 2016). There are many sources of feedback that teachers use to improve their teaching practices such as course grade, student evaluations, peer observations, training workshops, and student analytics. The OU is one of the few institutions that provided analytic tools for teachers on a large scale (Herodotou, Rienties, et al., 2019; Rienties, Boroowa, Cross, Farrington-Flint, et al., 2016). For example, OU Analyse is a tool that provides teachers with (near) real-time analytics of student behaviour (e.g., click count, submission record) and predicts academic performance based on data about students (Kuzilek et al., 2015). Since feedback and reflection is an essential step in the design process, the next RQ seeks to understand what kind of feedback teachers receive on their modules, and how they make use of this feedback. This also provides a bridge between subsequent studies (Chapter 6 and 7) which connected LD with student behavioural engagement.

- **RQ2.3** How do teachers make use of feedback on their module to support learning design?

The next section provides an in-depth overview of the methods employed in Study 2 to address these questions.

5.2 Methods

5.2.1 Setting and Participants

In order to discuss how the participants were sampled, it is important to first understand the context of the LD process at the Open University UK. In a traditional university, a module or a course is usually designed by a lecturer/professor who has the full autonomy to make decisions such as what to teach, how to teach, and how the course is scheduled (Biggs et al., 2007). In contrast, designing a module in a distance learning setting (i.e., OU) requires participation from multiple stakeholders (i.e., a production team) with several stages/checking points during the design process to ensure the consistency and quality of the module produced (Figure 22). Table 24 below provides an overview of the different roles in the module teams.

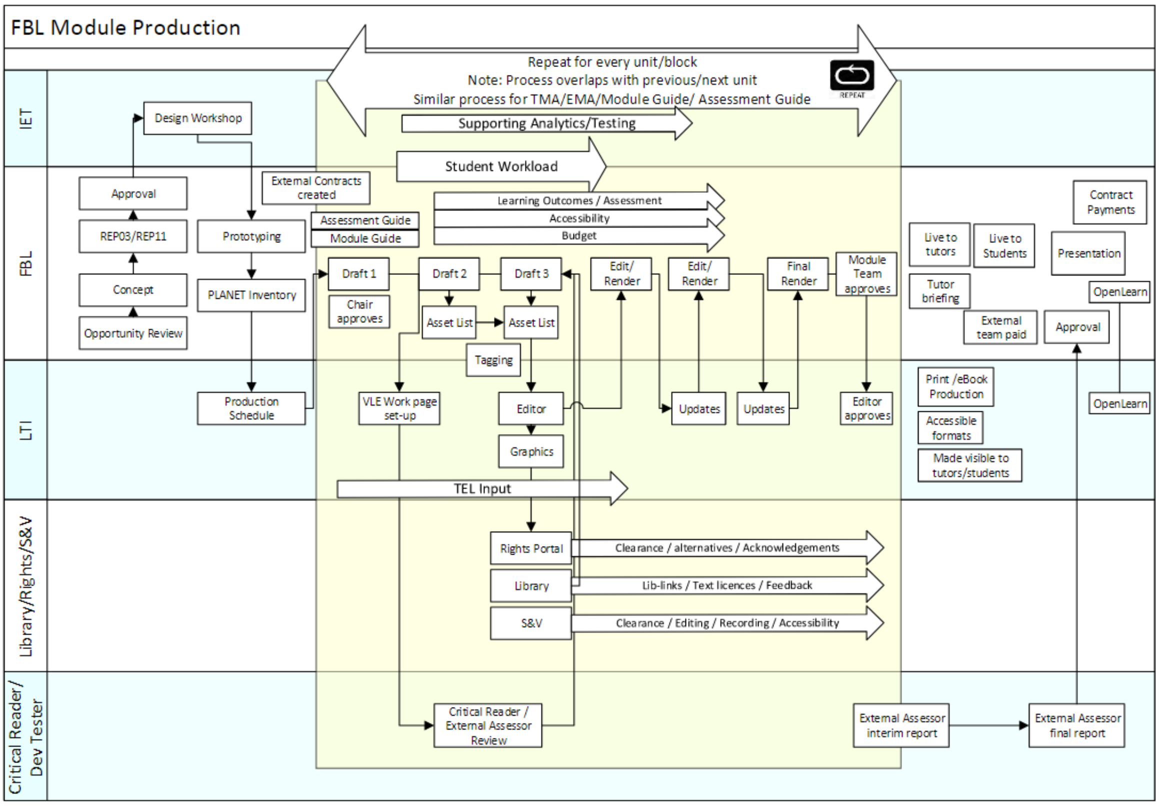


Figure 22. The module production process of the Faculty of Business and Law 2019[18]

[18] https://openuniv.sharepoint.com/sites/curr/fbl/fbl-compressed-production-project/fbl-compressed-production/Shared%20Documents/Forms/AllItems.aspx?id=%2Fsites%2Fcurr%2Ffbl%2Ffbl%2Dcompressed%2Dproduction%2Dproject%2Ffbl%2Dcompressed%2Dproduction%2FShared%20Documents%2FModule%20Production

Table 24. A summary of the module production team's roles[19]

Production team	**Role**
Module chair(s)	OU Module chair(s) have the responsibility of providing academic leadership to ensure the coherence, cohesion and quality of the learning experience offered by the module within the qualification(s) it belongs to. They have overall responsibility for the work of the module team and the setting and maintenance of academic standards
Academic staff	Authors who write the module materials and develop academic content Readers who critically assess the module materials
External assessor	A reputable academic subject specialist, usually from another university, with responsibility for ensuring that the academic standard of the module is consistent with the rest of the sector and acknowledges current thinking in the subject area.
Curriculum manager	Responsibility for project management and day-to-day administration of the planning, production and presentation of a module.
Module team secretary	Provide secretarial support for the module team
A member of the Institute of Educational Technology (IET), or the Learning and Teaching Solutions (LTS) if appropriate	Provide pedagogically advises on teaching strategies, using media, testing materials prior to the first presentation
Other staffs	External consultants, media project managers, media developer specialists (e.g., editors, interactive media developers and designers, sound and vision producers and media assistants working on activities such as text layout and rights clearance), subject information specialists and production and presentation administrators

[19] https://openuniv.sharepoint.com/sites/intranet-curriculum-management-guide/Pages/production.aspx

Table 24 illustrates that module chairs are responsible for making key design decisions, leading the production team and overlooking the module in its production phase and in presentation (i.e., when the module was running). Therefore, module chairs were selected as the participants of Study 2 because they are in a good position to offer valuable insights into the LD process (RQ2.1), their experience working with the OULDI framework and tools (RQ2.2), as well as how they make use of feedback on their module (RQ2.3). Study 2 specifically focuses on level 1 undergraduate modules (the equivalent of 1^{st}-year courses) because they account for the largest number of enrolled students. Furthermore, given the focus on retention strategic management, the OU has invested heavily in monitoring and following the LDs in year 1 (Herodotou, Hlosta, et al., 2019; Herodotou, Rienties, et al., 2019). In addition, this focus also allows me to triangulate the qualitative findings with quantitative findings from Study 1, 3, 4, all of which were also carried out on level 1 modules (Table 25).

In most cases, the module chair in production (i.e., when the module is designed) and in presentation (i.e., when the module is delivered to students) is the same person. However, in some cases in which the module was produced a long time ago, the module chair in presentation might not be the same person as the module chair in production due to the change of staff. In these cases, I tried to reach out to both module chairs to have a representative account of their experience in the LD process. Furthermore, in line with Creswell and Poth (2017), I continued to sample teachers until I reached a point of saturation, whereby limited new insights were added when new participants were added. There were 12 interviews in total taking place in 10 level 1 modules across a wide range of disciplines. Table 25 gives descriptive information about the modules selected in Study 2.

Table 25. Descriptive information about modules included in Study 2

Module	**Enrolments****	**Launched since**	**Credits**
Language	200	2017J	30
Computing 2	700	2017J	30
Arts 1	1400	2015J	60
Science	1400	2017J	60
Health*	1700	2015J	60
Computing 1	2400	2018D	30
Arts 2	2600	2015J	60
Business	2600	2015J	60
Education*	4000	2014J	60
Psychology	4900	2015J	60

* Two interviews, one for each module chair

** Number of students at 25% fee liability date in 2018 J (starting in October), figures were rounded to the nearest 100 for anonymization purposes

5.2.2 Procedure

The participants who were interviewed were identified from the module website which lists the contact information of the module chairs. In line with recommendations of Creswell and Clark (2017), the module chairs were then approached via email including the study information sheet (see Appendix 4), which allowed the module chairs to make an informed decision about whether or not to participate. Prior to the interview, a set of example interview questions were sent to the participants to give them an overview of the topics and the kinds of questions that would be covered in the interview. There was no financial compensation to participate in the interview. Upon arrival at the interview, the information sheet was summarised verbally. Informed consent was given via physical signatures at the bottom of the information sheet and was collected by the researcher at the start of the interview. All interviews were audio-recorded using a recording device with explicit verbal permission from the participant.

The interviews took place on the OU campus in a meeting room, except for two interviews taking place via Skype. Each interview lasted 45 minutes on average and was conducted in English. Participants were assured of the confidentiality of all statements during the interview and reminded that all identifiable information about the participants or the module would be anonymised.

The format of the interviews was semi-structured because it allows for key topics related to the research questions to be discussed while providing flexibility for unexpected themes to emerge from the interviews at the same time (Braun et al., 2012; Creswell & Clark, 2017) see also Chapter 3. Since LD in the OU context is an extremely complicated process, the flexibility of semi-structured interview format will be more suitable for unpacking nuances in module chairs' beliefs and experience in engaging with the LD process.

In line with Creswell and Clark (2017); Creswell and Poth (2017), the interview questions were written in a way that encouraged module chairs to discuss elements that they found most relevant to their experience in LD. For instance, broad questions such as "How do you design learning activities in this module" or "What are your experience working with the OULDI framework/tools" were drafted to minimise biasing participant opinions through leading questions. The interviewer's body language, tone of voice, and facial expressions were being kept as neutral as possible to avoid influencing respondents in such a way that it might distorts the outcome of the interview (Braun et al., 2012; Creswell & Clark, 2017).

At the beginning of the interview, participants were asked about their role and history of working for the OU in order to establish rapport and understand their background (i.e., prior teaching and designing experience at the OU). The interview was then divided into three parts that correspond to three RQs of Study 2. In the first part, participants were asked about the LD of the module and the LD process (RQ2.1). The interview questions were designed in order to tease out explanations, rationale, and opinions about their design decisions rather than merely describing what has been done. The second part of the interview explored participants' experience with the OULDI framework and tools (RQ2.2). Participants were encouraged to give examples of both the affordances and challenges that they encountered with the OULDI approach. In the third part of the interview, participants were asked to identify the various channels of feedback they received on their module design and how they made use of that feedback.

In order to practice interview techniques, as well as develop and test the suitability of the interview questions, two module chairs based in IET were selected to participate in a mock interview. At the end of the pilot interviews, the participants were asked a series of questions related to their understanding of the interview questions, their level of comfort with discussing interview topics and suggestions for improving the interview techniques. Research notes were taken to further refine the interview questions and interview techniques. The interview questions were checked by the supervision team and other experienced qualitative researchers in the department to ensure the clarity of the questions was appropriate (Figure 23).

Introduction
• Self-introduction • Explain the purpose of the interview • Asking for permission to start recording
Warm up
• Could you please briefly describe your role at the OU? • Could you please briefly describe the module (who is it for, what is it aiming to achieve)
Exploring learning design
• What do you want your students to learn from this module? • How do you structure the module? Why? • What kinds of learning activities have you designed in this module? • Why did you choose these activities? • Who were involved in the module's design process?
Experience with OULDI
• What is your experience with the OULDI? • What do think about the LD taxonomy? • How do you use OULDI in your design process?
Learning design and feedback
• What kinds of feedback or data that you received on your module? • What are your thoughts about receiving this information?

• How useful this information is? What did you with it/Any changes with the module? • Is there any additional information you would like to receive about the module?
Wrap-up
• Are there any other thoughts or experiences that you would like to share?

Figure 23. Semi-structured interview questions

5.2.3 Data Analysis

Thematic analysis was used to analyse the interview data to identify emerging themes of discussion that arose from the broad semi-structured interview questions (Braun et al., 2006). The analysis followed a six steps protocol as suggested by Braun et al. (2006, 2012).

1. Familiarizing yourself with the data
2. Generating initial codes
3. Searching for themes
4. Reviewing themes
5. Defining and naming themes
6. Producing the report

In the first stage of analysis, I transcribed two audio recordings in order to gain familiarity with the data and used a transcription service for the rest. Next, I re-read the interview transcripts and re-visited the audio recordings to immerse myself with the data while simultaneously making notes. In the second phase, all interview transcripts were imported into NVivo 11 to begin the systematic analysis of the data through coding. As suggested by Braun & Clarke. (2012), codes should go beyond the *descriptive* function of what the participants were saying, but also provide an *interpretation* about the data content. I went through the interview transcript and assigned both *descriptive* and *interpretive* codes for potentially relevant data to the RQs. During this stage, a list of 98 codes was generated. In the third phase, initial codes were revised, modified, and merged together if necessary. After that, emerging themes were identified by reviewing coded data for areas of similarity and overlap between codes. Themes should be distinctive but also need to work together as a coherent and compelling narrative to answer each RQ. This is an active process that combined both a *deductive* approach based on the LD conceptual framework by Dalziel (2015) and an *inductive* approach was used for generating themes. As a result, there were 12 themes emerged: 5 for RQ2.1, 4 for RQ2.2, and 3 for RQ2.3. At this point, themes and codes were given explicit definitions in a codebook, which served as a guide map for the coding process (Table 26).

Table 26. Summary and definition of Study 2 interview codes

Code	Definition of code
Teacher learning design	Codes related to how teachers designed learning activities and engaged in the learning design process. Statements related to:
Institutional factors	institutional policies and management decisions influence the learning design process of teachers
Study skills	teachers embedded study skills in their learning design
Student workload	teachers considered student workload in their learning design
Redesign/Codesign	the learning design was based on existing materials/modules or how learning design was a collaborative effort
Pedagogy	teachers structure learning activities such as readings, case studies, collaborations, assessment
Perspectives on OULDI	Codes related to the teacher's perspective on the OULDI framework and its process. Statements related to
Encouraging reflections, conversations, and new ideas	OULDI facilitates teachers reflect on their design, conversations across stakeholders and new teaching ideas
Management tool	OULDI was used as a management tool with a top-down approach
Process issues	the process of how OULDI was delivered to teachers such as the lack of follow up activities or the timing of the LD workshop
Interpretation issues	difficulties in interpreting and using the OULDI taxonomy
Feedback on LD	Codes related to how teachers make use of feedback on their module to inform their learning design. Statements related to:
Course evaluations	teacher's perspectives on course evaluations
Tutor feedback	teacher's perspectives on tutor feedback (ALs)
Analytics feedback	teacher's perspectives on analytics data about students

In the fourth phase, the coding scheme and the emerging themes were reviewed by the supervision team. Each team member coded two randomly selected anonymous interviews and compared their notes. This phase is essentially about checking the consistency and quality of the codes and themes generated. Any disagreements between two coders were discussed and the coding scheme was revised accordingly. In the fifth phase, each theme was explicitly defined to capture the essence of each theme in a concise and punchy manner. Finally, the analysis was transformed into an interpretable piece of writing with vivid and compelling extracts that form a coherent narrative to address each RQ. These narratives were then compared with the quantitative findings from Study 1 to draw the connections between LD representations and teacher perspectives. The combination of members checking and data triangulation with quantitative findings enhance the trustworthiness and credibility of the findings. All identifiable information about the participant and the module was anonymised in the report to protect participants' confidentiality.

5.3 Results and Discussion

The first section of the results reported LD figures of the selected modules in Study 2. It provided the basis to understand the current LD of these modules and subsequently support the interpretation of the findings with module chairs. There were missing data for four modules because they were recently launched in 2017/2018, which have not been mapped in the Activity Profile tool.

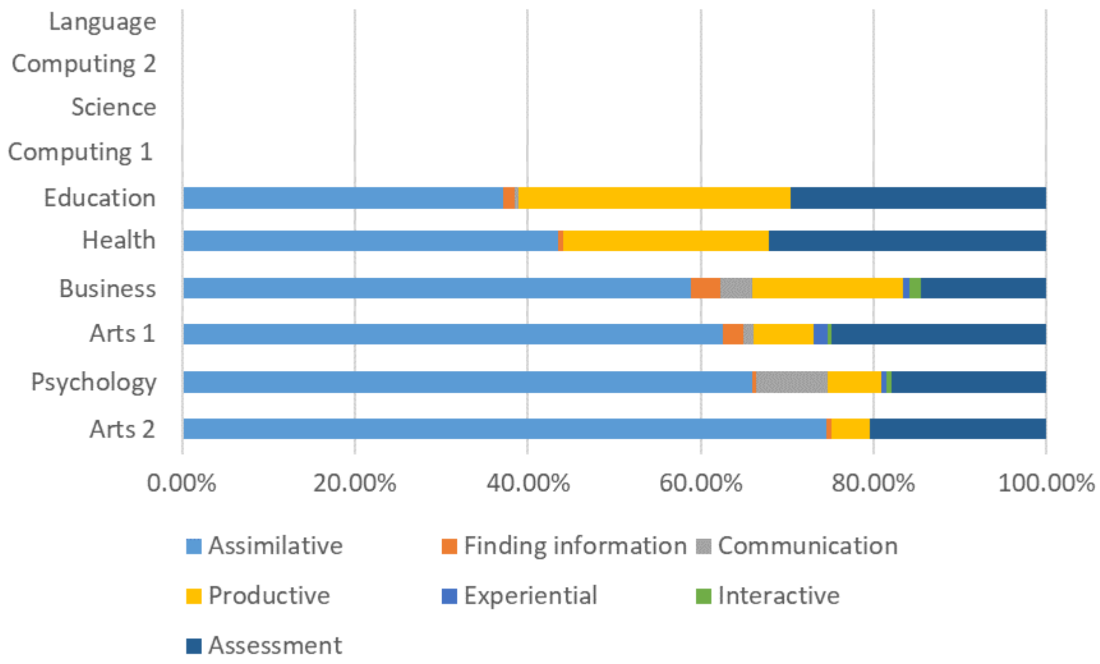


Figure 24. Learning design of 10 modules in the interviews

Note: Missing data from 4 new modules which were launched since 2017/2018

The six modules with available data in Figure 24 showed similar LD patterns compared to findings from Study 1, in which assimilative activities accounted for the majority of the total workload, followed by assessment and productive activities. Communication activities were present in the Psychology, Business, and Arts 1 modules. There were few or no communication activities in the Health, Arts 2, and Education module. Interactive activities were used in the Business, Arts 1, and Psychology modules. Finding and handling information activities were used with a low frequency in all six modules.

Overall, a total of 383 codes were recorded amongst 12 interviews. Table 27 summarised the frequency of each code applied and the number of interviews (i.e., sources) consisting such code. The emerging themes for each RQ will be discussed below.

Table 27. Summary of codes

Code	Sources	Code frequency
Teacher learning design	12	213
Institutional factors	10	27
Study skills	10	38
Student workload	10	52
Redesign/Codesign	10	18
Pedagogy	12	78
Perspectives on OULDI	11	107
Encouraging reflections, conversations, and new ideas	8	21
Management tool	8	15
Process issues	9	36
Interpretation issues	11	35
Feedback on LD	11	63
Course evaluations	9	17
Tutor feedback	9	15
Analytics feedback	10	31

Note: Source refers to the number of interviews that consists respective codes.

5.3.1 RQ 2.1 Results

Research question 2.1 aims at exploring the underlying factors that influenced the design process. The analysis of interview transcripts revealed five major themes, which are discussed below.

Theme 1: Learning design process was influenced by institutional factors

A consistent theme emerging through the interviews with module chairs was the influence of management and institutional policies on the LD process. Many participants reported that the design process was kickstarted by decisions from management.

> *'When the head of the department comes and knocks on your door, you know that it's never good news. And so I was told that [MODULE CODE] was needed a radical remake. It was already in remake, being led by a colleague of mine. And they decided that she wasn't doing the right kind of job and took it off her, which was so upsetting she decided to resign. So [co-chair] and I was given the role of remaking [MODULE CODE]. In terms of whether or not we... When you design a module, you never ever have free rein in what you do. Often the design is strongly influenced by the senior team at the beginning stages.'*
> (Participant 1, Health)

> *'The learning design, to a large extent, was dictated by university initiative. It had to be turned into 60 credits from two 30 credits. It was also done very quickly, as I understand it. So not having the blank sheet to start from scratch, it has never really been outcomes.'*
> (Participant 6, Arts 1)

The influence of management and institutional policies also restricted the autonomy of module chairs when making decisions about LD. Many participants mentioned that their LD decisions regarding assessment strategies were influenced by the recent change in institutional policy, so called single component assessment (SCA). The concept of SCA was first introduced in 2015 to support the OU's strategic objective to improve student retention and progression. Traditionally, OU modules included both a continuous assessment component such as tutor-marked assessments (TMAs) or computer-marked assessments (iCMAs), and an examinable component such as exams or end-of-module assessment (EMA).

> *'Originally we were told that we should have a portfolio at the end. And for TMA's and a portfolio and that this was something that was even, that was passed down from LTI (Learning & Teaching Innovation). We didn't have much say about it'*
> (Participant 3, Education)

> *'It was going to be one or the other, and modules would end with either an exam or an EMA, which would be an extended essay. So, very conventional. There had been a faculty decision that every module would include iCMAs, so we knew that we would be including an iCMA.'*
> (Participant 5, Psychology)

The SCA initiated an assessment strategy based on single-component assessment, whereby a student's module grade (including pass status) can be determined solely through a straight average of all the assessment tasks within one component. That usually means exams or EMA were replaced by a continuous assessment type such as TMA. After a few years of piloting, the adoption of SCA is made as a default approach for all level 1 and level 2 modules in 2018[20].

> *'Over the years, we have reduced the number of assessments and now students have 4 TMAs, which in line with the recent development at the OU (i.e., single-component assessment).'*
> (Participant 12, Language)

> *'Things to do with retention are big issues at the moment. Getting that information early and being able to respond to it is important. The problem is we've just had yet another institutional change forced on us in that we've just gone to single component assessment module, starting in 18J. I think students will add up how many marks they've got, and they will choose not to submit things when they've got accumulated their marks.'*
> (Participant 6, Arts 1)

Theme 2: Learning design process involved redesigning and codesigning

As part of the OU quality enhancement process, each module follows a life cycle review every 4-5 years. The purpose of the life cycle review is the review point for making a decision to end, amend or extend the life of a module. Most participants indicated that their modules were not designed

[20] QAC-2018-03-03 Consolidated policy for single component assessment
http://css2.open.ac.uk/ecms/get.aspx?object_id=090173b4816f0ad1&format=pdf

from scratch, and often involved redesigning an existing module or combining existing modules together. Learning materials and contents were often reused and adapted to the new module.

> *'The module is [MODULE CODE], kind of the third version of level 1 [subject] language and culture module, it was first produced in 1997 I was involved in the very first production of it. It was the then remade and now it's been made again but this time it wasn't just a revisioning but a full remake implementing a lot of curriculum and features.'*
> (Participant 12, Language)

> *'This was a 60-credit module, but we had kept a textbook from a previous 30 credit introductory module.'*
> (Participant 5, Psychology)

> *'[MODULE CODE] was designed from two existing accredited modules. When the university decided to [inaudible 00:05:17] the 30 credits in arts modules and go to a 60-credit pattern. It wasn't designed from scratch. Having said that, we needed to knit the two existing modules together.'*
> (Participant 6, Arts 1)

> *'It was called [PREVIOUS MODULE CODE], which was a 30-credit module, and I was chairing that, and then [MODULE CODE] came up as the replacement to turn it into a 60-credit module.'*
> (Participant 8, Business)

In some modules, the production process was a joint effort between two module chairs. The process of co-designing a module can offer a diverse set of perspective on LD as well as distribute the responsibility and workload more equally. Participants positively acknowledged the role of co-designer (i.e., co-chair) in the LD process.

> *'I co-chair with [CO-CHAIR NAME] and that's been really important because having two of us working on this module closely has been really productive in terms of trying to address issues like retention, progression, and getting beyond the day-to-day issues that come up and starting to looking into the future a bit.'*
> (Participant 4, Education)

> *'I don't know whether it's just standard practice in this school or in this faculty, but it's certainly something that I recommend. I think it's absolutely one of the most important things that you can do to ensure that you have a backup, you're meeting your deadlines, and you're resolving just tricky problems, is having that other person who is just as invested as you are in getting everything ready on time.'*
> (Participant 5, Psychology)

Theme 3: Developing study skills in learning design

The OU commits to provide equal opportunities to all students regardless of their background. Most undergraduate modules has no formal entry requirements. For this reason, the OU has an incredibly diverse population of students from different age groups with a wide variety of prior qualifications (Nguyen, Thorne, et al., 2018). Some students need more support than others because they left schools, dropped out many years ago and/or retired. This makes returning to an academic environment a daunting experience because they may lack appropriate study skills at a university level. Therefore, it is essential for LD at level 1 to build up students' academic skills in preparation for their learning journey at the OU. Most interviewed participants acknowledged the diversity of student profile and the need to scaffold an inclusive LD for all.

> *'What we're more worried about is the larger number of students for whom they would not have been in formal education for any length of time prior to this and may not have had sufficient preparation. They need to be able to have assessment tasks that are sufficiently demanding but they're accessible and understandable.'*
> (Participant 4, Education)

> *We have students who didn't realize that engineering had any maths in it. We have those students who did and were scared of it, and still hate it. And then we have those ones who are fantastic at maths, so a bit of my role is mitigating the tensions between those three groups, because there's one group, "This is easy. I've done this before." Then you've got another group, "I don't know what to do." So, that's part of it.'*
> (Participant 10, Computing 1)

> *'what we'd been asked to do was to rewrite it in such a way that it better scaffolded students who came to the module with few or no previous educational qualifications and would, for the first bit, be more of an access course in order to sort of induct them into higher education and then take them through. So, by the end of it they were pretty much good level one students.'*
> (Participant 2, Health)

> *'So, it's tricky in the sense that we have a few different groups of students. We have those students who didn't realise that engineering had any maths in it. We have those students who did and were scared of it, and still hate it. And then we have those ones who are fantastic at maths, so a bit of my role is mitigating the tensions between those three groups, because there's one group, "This is easy. I've done this before." Then you've got another group, "I don't know what to do." So, that's part of it.'*
> (Participant 11, Computing 2)

Most participants emphasised the need to gradually build up student study skills in parallel to subject knowledge to help them prepare for education at a university level.

> *'We redesigned the trajectory so that running across the entire module was a skills development strategy, in which throughout the module the students were taught how to perform a certain skill, and they had activities to perform that skill in the learning guide. So, for example, note taking, was one skill in the first block. And the other skill was paraphrasing and writing a summary. And so, students were taught to perform these skills, and then the assessment task at the end of the first block would take a piece of writing, and can you take notes from it and summarize the writing? Write it in your own words. So really, really ultra-basic, really, really simple, and what we were trying to do was build up, establish the building blocks of the components of essay writing.'*
> (Participant 1, Health)

> *'So, we realised quite early on that one of the things we absolutely needed to do was to embed study skills into the course and study skills. I mean, you know, academic reading,*

academic writing, how to write essays, how to find information. And so, we had long discussions about that in the course team.'
(Participant 3, Education)

'In terms of the keys things that we wanted to do, is so one thing that was really very much in the forefront of our minds was how do we prepare students for level 2 study and in particular this module was focusing on programming and problem-solving skills.'
(Participant 10, Computing 1)

Participants also underlined the importance of clarity and consistency in instructions for level 1 modules.

'And so those activities tend to follow a fairly predictable sequence, so generally speaking, we don't do a lot of mixing it up. We have a strong belief that what a student should do is, is know exactly what they're in for week by week.'
(Participant 1, Health)

'I think I tend to go from the idea that students need to have similar balances from week to week. So, I think it's useful for them in order, it's about the rhythm of studying, I think. They start one week, they do it, and then they can almost predict what they've got to do the next week and I think that can help them with planning.'
(Participant 2, Health)

'So, in terms of the design, it's making that accessible and very kind of straightforward. So, we make the tempo of the module very, very straightforward. We produced kind of readings. As in we wrote the readings, in terms of the material. And we're having an online spine.'
(Participant 8, Business)

Theme 4: Teachers highlighted workload as a key issue in learning design

Most participants raised concerns about students having too much workload. The majority of OU students have a full-time or part-time job and/or caring commitments in parallel to their study. Having too many learning activities or overcomplex activities at the beginning could be very off-putting to students, who might have just returned to studying after a long time.

'There's always just, there was too much material. And the usage complexity was extremely high. So, the module would bring together several sources of information, all contained in different books. So, the student would have to buy two books, and they would also have a resource book they'd have to read in addition to learning guide, and they would also have a CD, a DVD that they would have to watch.'
(Participant 1, Health)

'I remember very clearly the day we started. [Co-chair name] and I sat down and actually thought, "Well what is it that a student studying [Module title] needs to know?" That was what we thought in order to cut down the amount of module content because in its old days, it was 24 units I think, so students would get two huge boxes, which can be quite intimidating, and we also had a look at the assessment, which within the first week demanded that students write an essay, which we thought was too much for students initially.'
(Participant 2, Health)

'There were too many questions. I mean the study skills, the, you know, reading for academic purposes or writing for academic purposes. We were asking maybe 20, 25 activities in one study week. Which again, because it was 10 hours, they're often very short activities, but students just found that overwhelming.'
(Participant 3, Education)

Keeping a balance and consistent study workload is essential to student success at level 1 modules. Many participants mentioned that they have deliberately cut down the workload and reduce the complexity of instructions when redesigning their modules.

'So that was one thing, we reduced the learning, the usage complexity, we reduced the number of activities the students had to do. So, what they did was that, before, up till that point, [MODULE CODE] had quite a frenetic pace. So, at 22 activities per learning guide, the students were always moving around doing things and shifting gears. And I think that students didn't do the activities as a result. It was just too many for them to do.'
(Participant 1, Health)

'In the first two [presentations] we wanted to do that. One question per topic, but we quickly realised that was too much, and that was producing too much stuff and too much stress for both student and tutor. So, we actually changed that within first presentation.'
(Participant 9, Science)

Participants also proactively estimated study workload of their learning materials and keep it consistent throughout the weeks.

'We are very much encouraged to have the same workload each week, and I think that's what we have always done and are trying to do. It's useful to get advice sometimes in the middle of writing module. In our early draft, we try to put timing against everything. A while ago we even published this to students. This would take you so long etc. We kind move away from that because we know that some students take this much time and others take this much time so there are lot of variations. We also have developmental testing, a small chunk of study materials, and the testers say how long it took them. In early draft, we will put timing against activities, and the author brief would be to make the week exactly to that length. For example, if we work out that students should take 7 hours a week, then if you write a week, then the instruction to the author would be 7 hours, and they are encouraged to write suggested time for each activity.'
(Participant 12, Language)

'So, on the basis of that time we looked at okay so how many hours are then left to actually read materials and then we used the reading times that were provided? Because this is level 1 so it would be, I think 35 words per minute. To calculate a rough estimate of how many words there should be in each part. So, then authors were then really instructed to stay within that limit.'
(Participant 10, Computing 1)

Theme 5: Learning design varied across modules and disciplines

Participants indicated a wide range of learning activities were used in their module depending on the discipline and the content. For some modules, the learning pattern is relatively traditional. A typical week of learning activities often includes readings, listening, watching and activities that help student reflect on the learning materials.

> *'So generally, a week of learning would start off with some kind of activity which is designed to sensitize a student to a topic area, to place the topic area at the student's fingertips… and then there will activities that will involve some kind of assimilative work in which we explain an idea or a theory or body of knowledge, so an expository activity. And those expository activities could be asking them to go and do a bit of reading, or to go off and look at a piece of, find some reading on something. And then the flow will lead towards so sort of application type activity in which we would ask them to watch a, look at a case study and understand, apply a theory they've just read about to that piece of, to that case study.'*
> (Participant 1, Health)

> *'Quite a lot of reflection, quite a lot of, common jamming some ways, you know, old school, old style, you activities of, you know, here's a [inaudible 00:09:02], here's an idea from the reader chapter, what's your response to it? Typing into a free text box. And then when they'd type that up, then comments to the module team had written would come up below that.'*
> (Participant 3, Education)

Interestingly, the excerpts from the module chairs in Health and Education modules aligned with the quantitative figures shown in Figure 23. Both modules used a lot of productive activities (32% for Education, and 24% for Health). To put it in perspective, the average percentage of productive activities of 37 modules in Study 1 was 17.6% with a standard deviation of 12.4%. That means, the Education and Health modules reported here had 0.8 to 1.2 standard deviation higher in productive activities than the average.

In other modules, teachers made use of interactive activities, case studies, brainstorming, or quizzes. The excerpt from the module chair in Business module also aligned with Figure 23, which showed that the Business module had the highest percentage of interactive activities (3%) compared to the average of 2.2% in interactive activitites reported in Study 1.

> *'It's varieties. It's quizzes, a little bit of analysing new responses to quizzes, it's case studies, it's tutor group forum discussions. We also have one case study, which we filmed in Germany, which runs through that whole module. We've got a narrative. So, we say, okay, we've got a business here that students can look at, because it's kind of theme-based.... And what we thought, it'd be nice to have this case study that we keep on returning to.'*
> (Participant 8, Business)

> *'There'll be practical tasks, and home experiments, and interactives, and video content, and quizzes, and everything. There is a lot of interactive content in [MODULE CODE] …I think it will sort of fit with the skills-based of the module, because generally in the interactives activities, the students are doing something. So, they are learning by applying a skill or they are learning a skill by doing something. So, I mean you can't deliver that with books, that's always been part of the OU core, but I think this way just made a ... Helped make a richer experience for the students.'*
> (Participant 9, Science)

> *'We always start with something active, so we wouldn't start with giving information. It would always start with activating prior knowledge or bringing in their own experience. For*

example, we might ask students to have a quick brainstorm, or what they already know about the topic, or engage them in a mini interview. Then we would be very keen to make it clear to students how their learning is accumulated, so based on something they have learnt in previously.'
(Participant 12, Language)

Collaborative activities remain a challenge for most participants in their LD. While collaborative activities were perceived to be useful for student learning, they were not well received by students because of concerns about their grades depending on others.

'I think there is a problem about students taking up the opportunities to be doing things together online. Students don't seem to like very much the collaborative research work that they would routinely do somewhere else, particularly if they are concerned that their grade depends upon other people in their group performing.'
(Participant 5, Psychology)

'I mentioned that we had an assessment that was collaborative work [inaudible 00:26:18]. That was very badly received by students. They felt that their marks were being made dependent on other people responding… So, we changed the model of the assessment so that the mark for the collaborative work was reduced from, I think it was 60% originally, we gradually moved it, changed it. We introduced a much more individual component into that assessment so that students had 60% of that assessment would be entirely their own work.'
(Participant 6, Arts 1)

One participant also mentioned the resistance from tutors when they introduce collaborative activities. Interestingly, this finding also matched with Figure 23, which showed that there were no communication activities in the Health module.

'Yeah. It's missing because we took it out, and we took it out consciously. So, in the 2005/2006 version of [MODULE CODE] there was a collaborative activity that was regarded as disastrous by tutors, and by the module lead. And because we worked with tutors when putting together [MODULE CODE], that was one piece of advice we did listen to. And we removed it, and we never put any other genuinely piece of collaborative activity in the module... I was aware that the organization of collaborative work was always problematic because tutors never quite knew who was still registered in the module when it came to organize collaborative activity and assigning people. In the early days, 50%, sometimes up to 56% of the students would drop out of the module before the end. And so, if you're trying to organize collaborative activities when half your student body has left, it was really, really difficult for the tutors.'
(Participant 1, Health)

Other participants acknowledged the importance of collaborative activities in LD. However, they expressed that collaboration in distance learning is challenging and there are a lot of work to be done to get it right.

'I think that collaborative activity is one of those things which, yeah we just haven't got right. I used to say to my colleagues "I can't front up to any manager in [module discipline] and say oh no, we never expect students to work as a team," that's really wrong. [Module discipline' work is fundamentally team-based work. You have to communicate and cooperate with other people in order to achieve decent outcomes. And our modules don't do this very well.'

(Participant 1, Health)

> *'I don't quite think we got collaboration right. Collaboration between students in online environment, it's very difficult…They [students] just require to interact with each other. Just like discuss things on forums and things like that. And it's just the nature of OU students, I mean we have a lot of students who choose to study with the OU, so they don't have to go to a university and, you know, meet and even look at other people. And so, a lot of them are very adverse to just interacting. And they actually felt that they chose this degree, so they didn't have to. And so, for a lot of them, just ordinary communication is quite stressful. So, it's difficult because it's a requirement for progression in any scientific discipline ... Well in life, to be honest. But in any scientific discipline you have to work with other people. So, it's a learning outcome we can't really remove.'*
> (Participant 9, Science)

In summary, the LD process of module teams was influenced by multiple factors including institutional policies, student profile, and co-designing/re-designing. OU teachers scaffolded learning activities to build up study skills of their students, while making sure the workload was balance and consistent. There was a wide range of pedagogy used across modules and disciplines. Nonetheless, most teachers reported challenges in embedding collaborative activities into the curriculum due to the negative feedback from students and tutors.

5.3.2 RQ 2.1 Discussion

RQ 2.1 explored various factors that influenced how teachers made LD decisions in a distance education setting. In line with the existing literature (Bennett et al., 2015; Dalziel, 2015; Griffiths, 2017), a key finding that has emerged through all the interviews was the influence of management and institutional policies on LD decisions. One of the top institutional priorities at the OU is improving retention, which can also be generalised to other UK higher education institutions. As a distance education institution with an open entry policy, the OU attracts a large number of students from different academic and demographic backgrounds. However, the diverse population of students together with the flexibility of distance education resulted in a wide variation in retention rates. Rienties and Toetenel (2016b) reported that the pass rate of 151 OU modules ranged between 34.46% and 100%, with an average of 69.35% (SD = 12.75%). This could be a result of students switching modules, students did not complete the module, students failed to achieve the threshold for passing a module. Findings from Study 2 suggested three strategies that have been used in LD at the OU to address these retention issues: building up study skills, reducing workload, and single component assessment.

Firstly, participants emphasised the importance of building up student study skills at level 1 modules in parallel with subject knowledge. The OU offers a rich set of resources to develop study skills such as how to write an essay, how to find information, how to revise for exams, and computer skills[21]. These study skills are crucial to the development of OU students in general, but even more so with students who lack academic skills or have not been in an academic environment for a long time. For example, in a large-scale analysis of 123,916 undergraduate OU students in 205 modules from 2015 to 2017, Nguyen, Thorne, et al. (2018) showed that students with no formal qualifications or less than A-levels were 37%-50% less likely to pass a module than students with A-levels. Clearly, the prior educational background had a strong effect on the academic performance of OU students. Therefore, it is important to equip students with the necessary study skills to succeed in a distance education setting. The focus on developing study skills was also supported by the educational literature in self-regulated learning, which found that the ability to self-regulate one's learning process (e.g., goal-setting, planning, time management, revising) was positively related to academic success (Panadero, 2017; Winne et al., 1998; Zimmerman, 1990).

Secondly, student workload was another central aspect of LD at the OU (Chambers, 1992; Van Ameijde et al., 2016; Van Ameijde et al., 2018; Whitelock, Thorpe, et al., 2015). Module chairs in this interview study have highlighted potential problems of having excessive study workload or over-complex instructions on level 1 students. This finding was supported by Study 1 which showed a large variation in workload both within a module and between modules (Nguyen, Rienties, et al., 2017a; Nguyen, Rienties, et al., 2017b). To overcome this issue, module chairs have reduced the number of learning activities, removed non-essential content, and kept the instructions straight forward and consistent throughout the module. This decision was also supported by educational literature in cognitive-load theory, which showed a negative effect of information overload on working memory and cognitive process (Kirschner, 2002; Paas et al., 2003; van Merrienboer et al., 2010).

Thirdly, assessment design has been a core aspect of OU retention strategies which had a wider impact on LD decisions at level 1 modules. Participants mentioned that their assessment design was driven by the changes in OU's policy which made a single component assessment (SCA) a default approach since 2018 [22]. The premise of SCA is that students should be assessed in a consistent manner, either through continuous assessments or exams. As a result, most modules decided to remove the exam or EMA and replaced them with a TMA. The switch to an SCA strategy has been well received by the module team because it seemed to improve the retention rate.

However, the SCA strategy also has some limitations such as students might 'stop trying' once they reach the minimum average grade threshold to pass the course. The removal of the examinable component is controversial regarding what extent it can benefit student learning or it simply 'serves' the university retention figures. Another consequence of removing exams is to what extent

[21] http://www2.open.ac.uk/students/skillsforstudy/
[22] https://help.open.ac.uk/documents/policies/assessment-handbook

it would affect the credibility of the degree awarded to OU students. While summative assessment might not benefit students during their learning process as much as formative assessment, the former has an important role in checking a comprehensive understanding of students in a unit of learning. Removing exams might lower the standard of assessment and put the credibility of OU degree at risk, especially when it is compared to other brick-and-mortar universities.

Study 2 also revealed two unique aspects that are the by-products of the complex module production process at the OU namely co-designing and re-designing. The OU LD process is often different from a traditional university, where a professor/lecturer usually has full autonomy over the design process and the course content. However, module materials at the OU have to undergo a peer-review process by multiple stakeholders before they are officially used in the LD. Because of this long and complex quality assurance process, module materials were often reused until the new module cycle review comes in every 4 to 5 years. On the one hand, this process ensures the quality and consistency of the learning materials, which is beneficial to OU students. On the other hand, the rigidity of this process raised a question to what extent the OU module materials are up-to-date or can be updated without significant barriers from the quality assurance process. At the same time, because of this complex module production process, the OU module team is often made up of two or more academics. This co-design process was perceived to be useful by the participants because it offered new perspectives on LD, and progression and retention issues. For some large modules with thousands of students and hundreds of tutors, having more than one module chair means that the responsibility and workload can be shared amongst team members. However, this codesign process perhaps did not occur ‘naturally’ but as a combined result of the complex LD process and pressure for accountability from the management.

In terms of the pedagogy used in LD, there was a wide range of learning activities adopted by module chairs across different modules. In line with findings from Study 1, most participants mentioned the use of assimilative activities such as readings, listening, watching and productive activities such as analysing, reflecting, criticising. In some STEM modules, there were more interactive and experiential activities as the module chairs strongly believed in learning by doing/practising. Collaborative activities were perceived as important but challenging by most participants. Module chairs mentioned the resistance from students taking part in collaborative activities because the dependencies in grading and the resistance from tutors (ALs) to manage group works which can be time-consuming. This was again reflected in Study 1, which indicated only a small proportion of LD was dedicated to communication and collaborative activities. This is in sharp contrast to findings from Rienties & Toetenel (2016), who found that the primary predictor for student retention was communication activities. In other words, what students might enjoy and what is good for them might not be related.

This finding was supported by prior research in collaborative learning and online collaboration (Cherney et al., 2017; Kreijns et al., 2003). Some students may be entrenched with passive learning strategies and exhibit strong levels of resistance when they are asked to collaborate with each other. There are many explanations for this such as miscommunication (Kreijns et al., 2003), accountability problems (Cherney et al., 2017), and cultural differences (Mittelmeier, Rienties, et al., 2018). In online and distance learning setting such as the OU, the challenges for collaborative learning is even more salient because the students are complete often strangers coming from different background, age groups, communicating through asynchronous channels such as a VLE (Thorpe, 2002). Simply creating a medium for communication (e.g., opening an online discussion forum for a group of students) would not guarantee an effective collaboration experience. There are multiple factors such as group cohesion, trust, sense of community, and culture that should be considered (Kreijns et al., 2003). While the underlying factors behind successful collaborative learning are out of the scope of this thesis, I would direct readers to Cherney et al. (2017); Kreijns et al. (2003) for an in-depth review on this issue.

5.3.3 RQ 2.2 Results

After exploring the underlying factors that affected how teachers design their modules, this section will present findings from teacher experience engaging with the OULDI approach.

Theme 1: OULDI helps teachers to reflect on existing learning design and develop new teaching ideas

The OULDI framework and workshops have been perceived by many participants to be useful in reflecting on their existing instructional practices. The workshop is facilitated by the LD team, which takes the module team through a series of activities related to student profiling, module design mapping and quality enhancement. The workshop usually takes place at the beginning of the production process with the purpose of facilitating discussion amongst practitioners and encouraging module teams to think about different aspect of LD.

> *'In terms of the basic principle of learning design, I don't know anyone in the [MODULE CODE] team or in other times, that wasn't, that didn't see that these [OULDI] were a good thing. And as work through each element of the typology, having a conversation about each element of typology, articulating our view on it and how we're going to enact that, is a very useful thing for a module team to do.'*
> (Participant 1, Health)

> *'My experience with OU Learning design is from the initial briefings really, where you start to analyse the kind of breakdown of the course and the kind of objectives and the types of learning which is awesome. I think it's helpful to a degree. For folk who have not... it provides a very broad architecture, very broad structure, very broad framework, an initial framework for people to think about module design.'*
> (Participant 4, Education)

'It's really annoying. Now, I mean that in a positive way, because the time scale that we have for producing the module, didn't allow us to reflect. So, the way that we did the learning design process, we did it right in the beginning.'
(Participant 11, Computing 2)

Some participants also reported that the OULDI workshop was very useful in stimulating conversations across a wide range of stakeholders involved in the LD process.

'What module teams really like are the way that learning design pulls in all the key players from across the university. They love that. They love it that the TEL designer's there, the module chair's there, the library rep is there, the digital design editor is there, they like all of that. So that's the strength of the learning design process.'
(Participant 1, Health)

'I think it's helpful. I think it's helpful to get the team together. And I think it's helpful, it's certainly been helpful to me in this next team to think about the team more widely? I think there's always been a tension between thinking about the academics and the module team and then LTI.'
(Participant 3, Education)

Some participants also indicated that the OULDI framework and workshops help module team to consider a wider range of learning activities.

'The learning design workshop seemed to do was that it was trying to loosen up the few members of the module team to think more expansively about learning design. So, it seemed to me that one of the purposes of the learning design workshop was almost quite basically to think there's much more to teaching than getting students to read material. There's a range of things that you can do to help build student understanding.'
(Participant 1, Health)

'It's almost very helpful meeting with colleagues from LTI that they bring in expertise that is different from ours, expertise in teaching in online medium or they have done research university wide how students work with certain activity types. So that's very interesting for us. Which we then try to marry up.'
(Participant 12, Language)

Theme 2: OULDI was used as a management tool

Despite the perceived benefits of the OULDI approach as indicated in the previous theme, most participants voiced their concerns and frustrations about the OULDI process became a managerial tool. There was a mismatch between the original vision of OULDI and the actual practice which was dictated by the organisational bureaucracy. Participants expressed frustration towards the practice of OULDI as it has become a box-ticking exercise.

'Learning design's been extremely controversial in our school. And it's been extremely upsetting for our colleagues. And they've found themselves forced in a particular direction that they've neither endorsed, nor felt happy with. Because of the managerial role of our learning design.'
(Participant 1, Health)

'It becomes a tick box and it becomes something else the module chair has to do, you know, on top of an already incredible heavy workload. And you get a situation where you get people in LTI sort of saying, you haven't done this, this and this. They very rarely offer any practical solutions. It's just kind of criticisms of what you haven't done.'
(Participant 3, Education)

'And the learning design event is such a wonderful idea. Such a wonderful process, but only in our fake world, not in a world which is ruled by bureaucracy. It's really, really incredibly frustrating that we rarely get the chance to have everyone all sat down in a room. We've got everybody sat down in a room, and we've got a chance to do all of this wonderful, creative process, and what we're doing is filling in, basically using that time, to do contribute activities to fill in a form.'
(Participant 11, Computing 2)

As a result, participants found the OULDI too rigid and not flexible, which at times prevented the module team from their creative thinking process.

'So, you're not actually being creative, what you're doing is you're trying to appease the process. I feel the learning design event has been ruined by the fact that you're going oh, I like that, and taking bits, and saying well, that's now a requirement.'
(Participant 11, Computing 2)

'I can work with those categories, but I feel that when I'm working with them, I'm sort of ticking a box for other people rather than really designing. And you know, and I, you know, I certainly find it quite frustrating if we're been told, right, well you haven't done enough of that in one week. Because I think when you're not looking at, you know, when you put things in boxes and when you make tax on those, you can often miss the overall picture.'
(Participant 3, Education)

Theme 3: OULDI lacks follow up and practical suggestions

The OULDI workshop usually takes place at the beginning of the LD process. However, most participants indicated that there were no follow up activities after the initial workshop.

'I think the thing that is lacking in it, and it's exactly the reason why [co-chair name] and I aren't very familiar with it in this module, is that it happens at the beginning of the module. And then it doesn't happen again.'
(Participant 9, Science)

'Because I think it happens at a very early stage at the moment, initial meeting. And actually, it acts as a stimulus, and a helpful stimulus for thinking about learning design. But either a) it doesn't or b) I've just not seen it. I don't know how much it's then used through the actual production process. My suspicion is that it drops away then'
(Participant 4, Education)

'That [OULDI workshop] was great, but completely pointless because we didn't do it again.'
(Participant 11, Computing 2)

Some participants preferred the workshop to be taken place at a later stage in the LD process so that the module team has more concrete ideas about what they are going to teach and how they are going to teach.

'What we, I think we would have wanted it, actually perhaps is slightly later in the process, when we'd had more discussions. So, it was more focused on what [MODULE CODE] was, rather than generic learning design.'
(Participant 8, Business)

'We also have the problem that we did our learning design event before we knew what was in the module, because if there was, like the feeding in the module, hadn't been written yet. So, we didn't know what point they were going to get to.'
(Participant 11, Computing)

'Although you always try and write for learning outcomes, and so you're supposed to design activities for learning outcomes ... Ultimately, the narrative is in the texts which are about the content. The actual material. And it's just all too soon, really, to be able to ascribe numbers and time to producing a particular activity. When, you know, you might discover when you sit down to write the module, or write that material, that the activity just doesn't work. It's a bit of a tangent.'
(Participant 9, Science)

Participants also indicated a need for a more personalised approach with practical suggestions based on best practices or research rather than generic discussion on LD principles.

'We had lots of questions where we would have... it would have been very helpful if some, so we say okay, so we want to do this particular thing, what is the best way to do that? We had like I said things about how do you combine different medium or efficiently or more effectively? What are the studies on that? … We had people basically sitting in on all our meetings, what meetings sort of the formal ones, spending two hours. In the end we would say we have these and these questions and the next time they came back there were no answers.'
(Participant 10, Computing 1)

'What I would prefer was some, you know, people, you know, from the learning design team, be able to come up with some actual practical suggestions. Things that have worked on other modules, things that hadn't worked'
(Participant 3, Education)

'In a way, it might probably better to include some LTI colleagues in the module team early on, or to join a discussion at the beginning when we do discuss how we are going to structure our course into weeks, and having colleagues with that expertise in early meetings might be more productive than this big LD meeting.'
(Participant 12, Language)

Because of the early timing of the OULDI workshop and the lack of follow up activities, some participants pointed out that there are misalignments between the LD specification at the beginning and the actual LD at the end.

'My concern about learning design is the way in which when you're planning a module, you're having to actually say it's going to be this amount assimilative, this amount productive, this amount finding and handling, when actually in the writing of the module, that can change quite significantly. I think that's one of my issues.'
(Participant 2, Health)

'I think when it comes into detail, the modules take on a life of our own. I think learning design is a product of a particular way of thinking within the university. It's a reification, but it's a very, very generalised reification. It's not a very precise representation of what actually goes on and I think that's one of the things that's difficult within university, is to compare module design across the piece.'
(Participant 4, Education)

Theme 4: OULDI taxonomy is difficult to interpret

As discussed in chapter 2, the OULDI learning activity taxonomy categorises learning activities into seven groups: assimilative, productive, finding information, interactive, experiential, communication, and assessment. When asked about their experience using the taxonomy, many participants have voiced their concerns about how to interpret the activity categories with regards to their own module. Participants indicated that there were a lot of overlaps between categories of learning activity and the meaning of each category depended on individual interpretation.

'The characterisations are quite broadly interpreted, that I don't quite know how your team can look at a learning design characteristic and know that communicative activities in [MODULE CODE] mean the same thing as communicative activities in [MODULE CODE]. I think comparability of learning designs between modules is more problematic than we're prepared to. And IET's belief is, well you interpret it the way you want to interpret it. But that means that it's very difficult to consider these things more objectively.'
(Participant 1, Health)

'I think the initial, the learning design workshop, was helpful. I thought, I mean I think you share this with me, the sort of discreet categorization into these different types of learning activity. I think, I don't think that's necessarily extremely helpful to have these seven categories. Because they are way too fine-grained and what you get is just a long discussion about what each of the categories means. I would much rather think in terms of much more high level. In the first instance about what activities are really about doing things by the student themselves?'
(Participant 10, Computing 1)

'What I find really difficult, is actually the distinction. I think it's really quite useful to think about these categories, but when you're putting down the list, I quite often felt repeating myself, because for me it's all integrated. If I'm doing something, some of these are assessed, a lot of what we do involves communication, it involves production, it involves experiential activities, I wouldn't put them into "This is an activity, experiential one. Oh, this is the one that's being assessed." It's just when you fill in these forms it just does your head in, because ultimately, we're working really hard to integrate it all.'
(Participant 7, Arts 2)

Participants also mentioned that the estimation of duration for learning activities was challenging and varied across different types of learning activity.

'How long does it take a student to write an essay? I don't know, a good student might take 10 minutes. Another might take it in 10 days. You just don't know. You can come up with an ideal. But you can't predict. Things like creative writing, which is included in [MODULE CODE]. We're asking students to be creative. You cannot put a timeframe on creativity.'
(Participant 6, Arts 1)

> *'I mean sometimes with some of the activities, if it's word count, you're fine, because we've got those norms. But when it's activities, it's a little bit crazy. But then the critical readers happen. Some of the critical readers, we specifically point towards and say, actually did it take that long. I would rather err on the side of caution and give sufficient time.'*
> (Participant 8, Business)

In summary, participants showed mixed feelings towards the OULDI. While the participants acknowledged some benefits of OULDI in reflecting on their existing practices, they raised many concerns about the practical, ontological, political and organisational sides of OULDI.

5.3.4 RQ 2.2 Discussion

The second research question of Study 2 explores the affordances and barriers of teachers when engaging in the OULDI process. In line with previous findings in the LD literature (Cross et al., 2012; Griffiths et al., 2005; Hernández-Leo et al., 2018; Laurillard et al., 2018) teachers found the OULDI approach helpful in reflecting on existing the LD and brainstorming on new teaching ideas. Given the complex module production process at the OU, participants valued the benefits of having conversations across different stakeholders and exchanging expertise from different areas.

While most studies in the LD literature have reported on the 'positive' aspects of their LD framework and tool (Cross et al., 2012; Hernández-Leo et al., 2018; Laurillard et al., 2018), Study 2 made new contributions to the LD literature by uncovering the underlying barriers and challenges when implementing LD at scale. Module chairs in the interview have voiced their concerns about how the OULDI has become a managerial tool. Participants expressed frustrations when LD approach was forced down from the faculty level, which was treated as a form-filling exercise instead of thinking creatively about LD. The initial purpose of LD specification, which is a descriptive framework, has become prescriptive in a sense that faculty management prescribes the type of learning activities and the proportion of activities to the module chair.

This finding resonates with the tension between educational management and teacher autonomy proposed by Griffiths (2013, 2017). The author argues that "*LD offers a method for specifying the way that teaching should be carried out, and, to that extent, it offers a way of reinforcing top-down control of teaching activities by policymakers*" (Griffiths, 2017, p.123). Findings from Study 2 have confirmed this prediction, demonstrating how the OULDI, for some groups of teachers, has turned from a support tool to facilitate new teaching ideas to a management tool to ensure module chairs follow the module specification.

The author continues with "*It is not argued that LD has in fact led to a reinforcement of authoritarian educational policy, LD has not had sufficient adoption by governments and institutional managers to be able to bring this about. But it is proposed that teachers resist the extension of control* *which LD can be seen to imply*" (Griffiths, 2017, p.124). Interestingly, the OU is one of the few institutions in which the LD approach has been adopted across the institution. Results from Study 2 have supported Griffiths' argument showing how OU module chairs expressed frustration and resistance towards the use of LD tool as a straitjacket for OU management.

Participants also mentioned the difficulties in interpreting the OULDI taxonomy because of the overlaps between categories. This process of 'idealisation' of learning activities as discussed in Griffiths (2017) does not aim to provide a comprehensive description of LD. Instead, it prioritises certain aspects that were deemed to be the most relevant to the context in which the taxonomy was used. However, because the taxonomy was developed by individuals, it also reflects their own prioritisation of which aspect in LD is important and should be captured.

While the OULDI taxonomy was perceived as useful as a generic framework to start with, it was not able to provide concrete feedback and practical suggestions to module chairs in terms of designing their learning activities. There was also a lack of follow up LD activities after the initial LD workshop at the early stage of the production process. As a result, participants did not have the opportunities to further refine their LD as the module went through the production process. It is important for learning designers to work closely with the module team iteratively throughout the production process to identify the specific needs and provide personalised recommendations based on the module context.

Findings from Study 2 have crucial implications for the LD practices at the OU, and perhaps, other institutions who wish to adopt LD tools at a large-scale. While there are benefits in making teaching practices more explicit using LD tool, there are potential dangers of treating this tool as another measurement of teaching effectiveness for management and quality assurance processes. The pressure of having evidence of 'what works' in education can easily turn LD from a descriptive tool, as in its definition, an educational notation to a prescriptive tool 'what a good LD looks like', which is something that it was not designated for. As highlighted in Study 1 and subsequent studies in this thesis, LD visualisations and analysis of student behaviours can help educators narrow down their focus on potential problematic elements. These include a lack of collaborative activities, a peak in workload, or which learning activity that students were catching up on. However, this thesis does not attempt to prescribe what is a good LD, because there are many underlying factors that LD tools or LA tools cannot capture through its abstraction and simplification process. Instead, this thesis highlights potential problems in LD and encourages teachers to use the findings as a basis for their own quest to explore 'what works'. Educators must resist the temptation to find a silver bullet in teaching and learning (if that even exists), or at least, keep a critical stance and continue testing and collecting evidence from multiple data sources.

5.3.5. RQ 2.3 Results

After discussing participants perspectives on their own LD and the OULDI, this session will present findings on how teachers made use of various channels feedback on their LD.

Theme 1: Tutors are a main feedback channels on the module, but the quality of feedback varies

When being asked about the feedback that they received on their module, most participants pointed out that tutor forum (i.e., ALs) is one of the key channels. In each module, tutors are assigned to a group of students to provide feedback through marking assignments and answer any questions a student might have and to provide feedback through marking assignments.. A tutor forum is designed to facilitate communication between tutors and module chairs. Having direct interactions with students, tutors were able to voice their concerns as well as to provide near real-time feedback on seemed to works in the LD.

> *'We reviewed that, along with associate lecturers, we set up a focus group. We consulted with associated lecturers, we talked to them about what they perceived the issues were and we compared that with our own perceptions and where they met, we made interventions.'*
> (Participant 4, Education)

> *'We've got very active AL forums. If there's the slightest hint of something going wrong, the ALs will tell us about it automatically. It's a very good avenue. We have two AL reps who monitor that forum. They got onto me very quickly if there's something that's perceived as being a problem. Even things like a typo in the assessment, the newest assessment. They will tell you. We have a very good network of ALs who will feedback.'*
> *'The key channels informally are through the tutor forums, so the key forum. We're very present on the tutor forums. We can get kind of real-time feedback about what's working.'*
> (Participant 6, Arts 2)

However, some participants also were also cautious about how to interpret tutor feedback because it was not always helpful and sometimes represent personal opinions, beliefs, and biases.

> *'It [tutor forum] varies immensely in terms of the quality and helpfulness of the feedback. A lot of tutors we just don't hear from. You know they're just silent, they're not on the forums at all. Some are always providing helpful feedback, others it's just snippy complaints that really aren't helpful at all. You know, one or two you think they're just out to try to prove themselves, that they know better than we do. There's two that are like that. Then others slightly use the forums to chat really, and that's a bit annoying when you have to check their posts to see if it's for you.'*
> (Participant 6, Arts 2)

> *'Tutor feedback I feel really ambivalent about. Because I don't think that the feedback that we get from tutors is as direct and un-reinterpreted source of feedback. So, tutors, for example, would argue that [MODULE CODE] really needs an exam. It's good for students to have an exam, the students who go through the exam benefit from it, there are lots of good reasons why our module should have an exam. We listened to them and their advocacy of having an exam. We put an exam in place, and we lost more students than we should have. We removed the exam, we improve retention by 5% automatically, and we subsequently learned that if you have an exam, 10% fewer people will even turn up, compared to an EMA.*

So, tutors have particular beliefs about ideal educational conditions, and they'll advance those thinking that they're in the students' favour.'
(Participant 1, Health)

'However, we also get a lot of information through the tutors. Sometimes that kind of information can conflict with the information we get. For example, last year we have very high satisfaction rate but the tutor feedback last year, students were struggling, they find it hard.'
(Participant 12, Language)

Theme 2: Teachers find open comments in course evaluations helpful, but recognise the potential biases in self-report surveys

Participants pointed out that course evaluations (i.e., SEaM student surveys) are a main source for KPIs of module performance. Open comments were perceived by the participants to be more helpful than numeric data from SEaM.

'I always try and look at the free comments, because I think they're far more telling than the responses to the multiple-choice questions, because I think the multiple-choice questions are designed to elicit certain responses. Which may not be the ones that help us really engage with that students like and dislike, and you know, how the world is behaving.'
(Participant 6, Arts 2)

'I find that actually, on a high-level quantitative feedback, oh it's okay but often it says we're doing okay. We can still do better, but we're doing okay because the module has gone well. But there... some of the qualitive feedback was helpful, because you can go through and identify patterns and see what students are really focusing on.'
(Participant 8, Business)

Some participants find it difficult to navigate through the open comments because of the mixed responses from students.

'You go to open comments and there are reams and reams and reams, as you can imagine [inaudible 00:49:12]. A student might say, "I really enjoyed the way in which the assignments were structured. I really appreciated all the guidance." 25 students might say something similar. Another 25 students will say, "I hated the assignments. I hated the way it was structured. This has no relevance to me whatsoever.'
(Participant 4, Education)

'So, feedback comes from the SEaM survey. Uptake is relatively low, the questions are relatively broad, the free texts is generally moaning… the negative comments we got we pretty much all anticipated…So we are step up in intensity from the introductory modules, we have to be. May have to be nice and gentle, they have to be. So, we anticipated they're going to say there's too much work. And then, because we do cover five disciplines, there's always going to be some students who say, "I don't like this.", "I don't have any interest in that. Why do I have to study it?" You know, we knew that was going to happen.'
(Participant 9, Science)

Some participants raised concerns about the credibility of the course evaluations due to low response rate. Participants were also cautious about the open comments because they only attract students from two extreme ends, either very happy or very upset.

'Let's say we've got 20% of people submit the SEaM survey, and they all say the same thing, that's another thing, but when one student says this is too easy, and another students says this is too hard, and I'm asked how am I going to deal with both of these, it's just person out of the whole thing. Okay, if half of the SEaM survey said it was too easy and half said it was too hard, okay maybe we've got a population there, and these are the people at the ends of bell curve, and we need to deal with them. When it's just one person out of 400, but they think what are you going to say? It's just a waste of time.'
(Participant 11, Computing 2)

'So, every module review that comes in, nearly every module review that comes in, [tutors] will say, will use the same phrase. And that is "the SEaM results must be treated with caution because the response rates are low." Or they might say something, and I'm sure that this will make your ears prick up, "the SEaM results need to be treated with caution because they're not significant." They've never done a statistical test on them, they've got no measure of significance, but once again they say the response rate's too low.'
(Participant 1, Health)

Because the course evaluation results were not available to the module team until the end of academic year, some participants found it difficult to act on the feedback given the short timeframe.

'So even if you get SEaM results in July or August, you have no time to change the module. In fact, in the first presentation of a module, so the module will start in October, and then by April the following year, you'll need to have an assessment booklet for the next presentation written, before the students have finished the module. Basically, our production cycles and our maintenance cycles are out of sync with module productions. Our presentation cycle is completely lacking in agility.'
(Participant 1, Health)

'What I would like is more direct feedback from all the tools, things like TMA submissions. Just for our retention. Retention is still a problem. We often get that information too late to really do anything about it.'
(Participant 6, Arts 2)

Theme 3: Teachers found analytics data helpful, but were critical about the data

Many participants pointed out that they have frequently used analytics data available from the SAS-VA, a data visualisation tool available to OU staffs which provides information about student profiles, module KPIs and engagement data. Examples of data from SAS-VA include number of registrations, number of TMA submission, pass rate from the previous semesters, demographics breakdown of students enrolled in the module.

'Well, SAS-VA I tend to use it for who's still registered and TMA completion and that sort of thing. I think it's great actually. I'm really, really pleased with it. I think to be able to have that at your fingertips rather than, I can't remember the old thing we used to... the module performance. Module profile tool was the old thing they used. But, yeah, I think that's a really helpful tool and I guess if that could be used for garnering more student feedback, that wouldn't be a bad thing as we go along.'
(Participant 2, Health)

'So, analytics, I'm completely obsessed with it, but and I love it and I get it. I wake myself up at 2 o'clock in the morning when the servers refreshed so I can check to see how things have changed, that's how obsessed I am with it.'

(Participant 11, Computing 2)

‘In the early weeks, as part of the PDP, the personal development planning, there's an activity which includes a questionnaire and that questionnaire then leads on to the completion of learning journal number one. Okay? Through the dashboard, through the SAS-VA go in at week four and look to see how many students have completed it. And just that single bit of data gives us really, really concrete sense of the level of engagement that students are having with the module.’
(Participant 4, Education)

Some participants indicated that they want more fine-grained analytics data on their module

‘The visual analytics for me is probably the most important. What it doesn't do, and what I can't pull out of it myself, though I'm sure somebody somewhere could. One of the things that's concerned me is the number of students who don't engage with exam preparation rules. Something like a quarter of students actually go online and look at the exam preparation materials, and what I want to find out is where are the other 75%, and why aren't they engaging, and hits on a database, you know, on an online website, tell me that.’
(Participant 6, Arts 2)

‘I think the amount of analytic data we have available is amazing. I know colleagues at other universities that would kill to have the amount of knowledge of students that we do. There are things I'd like that we don't have. I'd like it to be a lot easier to see what individual students are doing. So especially as we're very ... There are so many different parts through our module. And there's so many different topics. I want to know where the students are studying every topic. I want to know where the students are studying all of the earth sciences topics, or whether they're not. And that's very difficult to get. In fact, I don't think it's possible currently.’
(Participant 9, Science)

While most participants found analytics data useful, some participants were cautious about the quality of data and how to interpret the analytics.

‘Yeah, and also, are those hits that website, yes, they are logged as individual hits, but are they, actually, individual students who are spending a certain amount of time engaging with that visual, or are they sitting on it and going away?’
(Participant 9, Science)

‘The analytics is pretty much real time, but you need to be able to interpret the analytics in relation to student behaviour. So, you should never ever check TMA submission rates the day after the TMA is due, because there's always a three-week lag that will pick up 50% of the students. The SEaM survey results, so the module will end in July, SEaM survey won't appear until August or September. ‘
(Participant 1, Health)

One participant was particularly concerned about the quality of learning analytic algorithms and want to have the ability to dissect the data himself.

‘No, because I don't trust [predictive modelling]. I only trust it if I do it myself. Because then, there's so much in OU Analyse which is hidden compared to what not hidden, so I can't then decide what he's saying, there's not. There's so many things in terms of the statistics that

OU uses, which is horrendously poor, that I don't trust the statistics that anyone might have done if they're going to hide the statistics from me.'
(Participant 11, Computing 2)

5.3.6. RQ 2.3 Discussion

The third research question of Study 2 investigated how teachers made use of different feedback sources on their module design. Three channels of feedback were identified, namely course evaluations, tutor feedback, and analytics data.

While course evaluations provided important KPIs on the module, they also received a lot of criticism from the participants regarding response rate and the interpretation of open comments. The limitations of self-report for course evaluations have been extensively discussed in educational literature (Richardson, 2004, 2005). A major problem with the course evaluations is that they only represent the output of learning, while giving limited insight into the process (what, how, when students study). This problem becomes even more prominent in an online learning environment, in which face to face interactions are much more limited. Open comments of course evaluations were perceived to be more useful than numeric data by the participants. However, there are challenges in analysing the open comments because of time constraint, as well as the interpretation issues. Recent developments at the OU have tested machine learning approaches to support teachers analyse open comments from course evaluations (Ullmann et al., 2018).

Tutor feedback was another major source of information on module design. Because tutors interact with students frequently, they were able to detect problems in "real-time" and communicate these problems directly to the module team via a tutor forum. Most participants highly valued the quality of tutor feedback. However, module chairs also recognised potential biases in tutor feedback as it could reflect personal opinions and beliefs.

All participants found analytics data helpful in managing their module because they provide a direct channel between the module team and the students. Most participants actively made use of SAS-VA to check submission rate or check the level of engagement on a particular learning activity. This finding resonates with recent evaluation studies of OU Analyse which showed a positive impact of LA tool on student retention (Herodotou, Hlosta, et al., 2019; Herodotou et al., 2017; Herodotou, Rienties, et al., 2019). Some module chairs also expressed their demand for a more fine-grained analysis of student learning patterns. These findings are well aligned with the rationale for the next studies in this thesis, which connected LD with learning behaviour at a fine-grained level.

5.5 Conclusion

In conclusion, Study 2 has explored the teacher's perspective on the LD process, OULDI framework, and analytics data based on 12 semi-structured interviews with level 1 module chairs at the OU.

The study offers unique contributions because it triangulated findings from a teacher perspective (qualitative) and LD representations (quantitative, Study 1) to understand how teachers design for learning in distance education. In addition, Study 2 took a further step to not only explore the affordances but also barriers when LD approaches were implemented at scale. It provides valuable lessons for the OU to refine their LD practices and for other institutions who wish to implement LD in the future.

There are some limitations of Study 2 which should be mentioned. Firstly, Study 2 took place at a distance education institution and focused on a small number of level 1 modules. Therefore, readers should take a critical stance when generalising their findings. Secondly, the findings of Study 2 reflect the researcher's own biases in interpreting the data. Thirdly, because most modules in Study 2 were produced in 2015, the findings might reflect participants experience at the time, which might or might not applicable to recent developments in the OULDI practices.

Study 1 and Study 2 together have laid out the foundation to understand how teachers design for learning at the OU. These two studies have provided empirical evidence on the overall patterns of LD at the OU as well as the underlying factors that influenced teacher design decisions. However, an important missing piece of the puzzle remains is how students engage with LD because that is where learning happens. As argued in chapter 2, the connection between LD and LA could help teachers validate their assumptions in the LD, to compare 'what teachers expect students to do' versus 'what students actually do'.

The next chapters will take a step forward by linking LD with student learning behaviour. The next studies are important because they provide empirical evidence of how students learning behaviours were influenced by the way teachers design their modules. Study 3 presents a large-scale analysis of 37 module designs and behavioural patterns of 45,190 undergraduate students at a weekly level. Study 4 showcases a deeper analysis into the relationship between the timing of engagement and academic performance of 289 students in one module replicated over two semesters.

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Chapter 6 - Study 3 Impact of learning design on student engagement, satisfaction, and pass rate [23]

Study 1 and 2 have provided empirical evidence of how teachers designed their modules at the OU. Study 3 takes a step further by examining how LDs influence students' behavioural engagement in a virtual learning environment. Section 6.1 – Introduction summarises the rationale of the study and presents its research questions. Section 6.2 – Methods describes an overview of the specific methods used in Study 3, including information about the setting, participants, instruments and data analysis approach. Section 6.3 – Results presents the findings in relation to each research question. Section 6.4 – Discussion discusses the implications as well as limitations of Study 3 and provides connections to the subsequent studies.

6.1 Introduction

Recent years have witnessed an increased interest to leverage Learning Analytics (LA) to inform and support Learning Design (LD) (Lockyer et al., 2013; Mor et al., 2015; Persico et al., 2015). One of the main benefits of aligning LA with LD is that LA could act as a reflective resource on how students actually behave compared to teachers' assumptions embedded within their LD, which has been echoed by many scholars (Dalziel et al., 2016; Gašević et al., 2016; Mangaroska et al., 2018; Mor et al., 2015; Rienties et al., 2017). For example, Persico et al. (2015) 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 et al. (2015) suggested that LA could facilitate teacher inquiry by transforming knowledge from tacit to explicit, and perceive students and teachers as participants of reflective practice. Griffiths (2017) viewed LD and LA as process that both create and implement models of learning processes, in which LD models teaching practices and LA models student activities.

Several conceptual frameworks aiming at connecting LA with LD have been proposed. For example, Persico et al. (2015) discussed three dimensions of LD that can be informed by LA: representations, tools, and approaches. Lockyer et al. (2013) 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 students are carrying out their tasks. In the LAK conference 2016, Bakharia et al. (2016) proposed four types of analytics (temporal, tool-specific, cohort, and comparative), and contingency and intervention support tools

[23] The empirical investigation undertaken for this chapter has now published as:
Nguyen, Q., Rienties, B., Toetenel, L., Ferguson, R., & Whitelock, D. (2017). Examining the designs of computer-based assessment and its impact on student engagement, satisfaction, and pass rates. *Computers in Human Behavior, 76*, 703-714.

with the teacher playing a central role. All of these conceptual frameworks pointed towards the importance of embedding student data into the LD process, which is the rationale of Study 3.

Although there are numerous conceptual discussions on the link between LA and LD, the number of empirical studies on this topic has been rather limited (Mangaroska et al., 2018). For example, in a large-scale study of 151 modules and their 111,256 students at the OU, Rienties and Toetenel (2016b) found significant relations between LD and VLE behaviour, along with student satisfaction, and retention. The findings showed that by taking the context of LD into account could increase the predictive power of student behaviour by 10-20%. Gašević et al. (2016) compared the predictive power of trace data on academic performance of 4,134 students following nine first-year courses from a public research-intensive university in Australia and showed that the effect of learning behaviour on academic performance varied significantly across different instructional conditions.

While these studies have provided important markers to the field of LA and LD, they have not considered the temporal characteristics of LDs and student behaviour. As illustrated in Study 1, LD is a dynamic process changing over time with a wide variation in workload and learning activity types. One of the unique advantages of trace data is the ability to track learning activities with a timestamp, which makes it suitable for investigating temporal learning process of students (Chen et al., 2018; Knight, Friend Wise, et al., 2017a).

Moreover, Study 3 contributes to the data triangulation of LD. Study 1 examined LD from a data visualization perspective, Study 2 explored LD from a teacher's perspective, and Study 3 will investigate LD from a student's perspective. By triangulating three different sources of data, Study 3 contributes to the holistic understanding of LD and the robustness of the findings.

Therefore, Study 3 addresses the following research questions:

RQ3.1. How do learning designs influence student behavioural engagement over time?

RQ.3.2 How do learning designs influence student satisfaction and pass rate?

6.2 Methods

6.2.1 Setting and Participants

Study 3 took place at the OU, as did all the other studies which are reported in this thesis. The OU is the ideal context to answer Study 3's RQs because it has a wealth of data about a) student performance, demographics, and online behaviours and b) extensive information about LD as illustrated by Studies 1 & 2. Furthermore, by operating in the same context, Study 3 will support the data triangulation process with Studies 1 & 2. Further details about the OU as a study context can be found in section 3.3.1.

To answer RQ3.1, two data sources were needed namely LD data and student engagement data at a weekly level, which will be described in detail in Section 6.2.2. Firstly, the LD data were based on Study 1, which consisted of 37 undergraduate modules. Secondly, the student data were collected based on the LD data from 37 modules, which resulted in 45,190 registered students in these 37 modules. There were more female students (57 %) than male students (43 %) studying these 37 modules. The majority of these students were from the UK (96%) and declared their ethnicity to be 'white' (87%). Students varied considerably in age, with 27% under 25 years old, 35% aged 26-35, 20% aged 36-45, 12% aged 45-55, and 6% aged 56 and over.

More than half of the students were working full-time (52%), while 19% were working part-time, 8% were looking after the home/family, and 6% were unemployed and looking for a job. Regarding students' qualifications, there are no formal academic entry requirements at the undergraduate level at the OU. In Study 3, 41% of the students had A levels or equivalent (suggesting they had two or more years of post-compulsory schooling), 33% had less than A levels (suggesting they had not progressed beyond compulsory schooling), 20% had higher education degrees, 4% had a postgraduate qualification, and 3% had no qualifications. On average, 10% of the students had a reported disability.

6.2.2 Instruments

LD mapping

The LD data were retrieved from Study 1, which grouped learning activities into seven categories: assimilative, productive, communication, finding information, interactive, experiential, and assessment. The seven types of learning activity were measured in terms of the duration in hours that was allocated for each type of activity. For a detailed description of the mapping process and reliability of this approach, see section 4.2.2 and 3.2.2.

Online behavioural engagement

In Study 3, the time spent on the VLE (i.e., Moodle) was used as a proxy of student online behavioural engagement (see section 3.3.3. for the rationale and limitations of this measurement). The average time spent was calculated from the trace data, which were retrieved from the data warehouse at the OU. This is a central database that stores all information related to OU students such as demographics, performance, finance, and online behaviour. In this dataset, the system recorded the time spent and the number of visits for each student on a daily basis. There were more fine-grained data available, such as information about the type of content, learning materials, device accessed, which will be explored in Study 4. However, the focus of Study 3 was to conduct analyses at a macro level across 37 modules. In order to link LD data with engagement data, the measurements needed to be on the same level of analysis (e.g., weekly). Based on this, two measurements of behavioural engagement were generated:

- VLE per week: Average time spent on the VLE per week (in minutes)
- VLE per visit: Average time spent per visit on the VLE (in minutes)

Study 3 extracted data from the week -3 until week 40 (data streams typically start three weeks before the official start of the module) in order to merge with the LD data. While the use of time-on-task is common in LA research (Kovanovic et al., 2016), there are many caveats with this type of data that should be acknowledged, which are discussed in section 6.5 Conclusion.

Satisfaction

Since its foundation nearly 50 years ago, the OU has consistently collected student feedback in order to improve the students' learning experience and subsequently improve LDs. This work is embedded within the quality assurance and quality enhancement procedures of the OU. The Student Experience on a Module (SEaM) survey was employed as part of the quality assurance process (Li et al., 2017a), just as with other student satisfaction instruments (Onwuegbuzie et al., 2007; Zerihun et al., 2012). This standard questionnaire is sent to all students who are still registered at the end of the module.

Following a previous study of key drivers of the learning experience of 115,000 students (Li et al., 2017b) who found significant relations between overall course satisfaction and factors related to LD, Study 3 used the aggregate scores of five core items (out of 40) from the SEaM survey that have been shown to drive student satisfaction. These five items measured students' satisfaction with regard to (1) teaching materials, (2) assessment on module studied, (3) advice and guidance provided for module study, (4) integration of materials, and (5) career relevance, scaling from one to five in which one means "definitely agree", and five means "definitely disagree".

Pass rate

The pass rates for each of the 37 modules were calculated as the percentage of registered students who completed and passed the module.

6.2.3 Data analysis

The main purpose of the analysis is to identify any statistical relationships between LD and student engagement. A naïve approach would be to run a normal regression with student data (i.e., engagement) as dependent variables and LD data as independent variables. However, as shown in Gašević et al. (2016) and discussed in section 2.3.2, the effect of learning behaviour on student outcome varies from courses to courses. Therefore, it is important to control for the heterogeneity between different modules. For this reason, a fixed-effect regression model was used in Study 3.

A fixed-effect model is a common statistical technique often used to analyse panel data, in this case, 37 modules over 34 weeks. The idea of a fixed-effect model is to control for the time-invariant heterogeneity between modules by incorporating a dummy variable for each module. In other words, the model controlled for fixed characteristics of each module that do not change over time such as the number of credits, module-level of study, etc. This can be formalised as follows:

$$\text{Engagement}_{it} = \alpha_i + \beta_1 * \text{Assimilative}_{it} + \beta_2 * \text{Productive}_{it} + \ldots + \varepsilon_{it}$$

- Engagement_{it} is the level of engagement of module i in week t
- α_i (i=1…37) is the unknown intercept for each module (37 module-specific intercepts)
- Assimilative_{it} is a level of assimilative activities of module i in week t
- β_1 is the coefficient for Assimilative
- ε_{it} is the error term

In preparation for the fixed-effect model, a Hausman test was used to differentiate between a fixed effect and a random-effects model. This test checks whether the coefficients estimated by the random effects estimator are the same as the ones estimated by the consistent fixed effects estimator (Hausman, 1978). The results supported the assumption of correlation between observation errors and predictors. For this reason, a fixed-effects model was used as it removes the effect of time-invariant characteristics to assess the net effect of the predictors on the outcome.

Variance inflation factor (VIF) was computed after each model to check for multicollinearity. All VIFs for the predictors were smaller than 2.00, indicating there was no significant correlation among the independent variables. In other words, there was a little overlap of measurements among seven types of learning activity. Study 3 report unstandardized coefficients because all the explanatory variables were measured in the same unit (hours). Thus, it was more informative to report the original metrics. The analysis and visualizations were performed using Stata 13 and Tableau 10.1.

6.3 Results

6.3.1 Learning design and engagement

Figure 25 visualised the average time spent on VLE per week against the expected time spent on seven learning activity types. In line with Study 1, the overall patterns demonstrated the dominance of assimilative (orange), assessment (blue), and productive (grey) activities. What was new in this visualisation was the time spent on VLE by students. On average, students spent 116.3 minutes on the VLE on a weekly basis (SD=66.35) (Table 28). In each visit, students spent on average 22.9 minutes (SD=8.61). There was a sharp decline in week 11 and 12 which represented the Christmas breaks. The level of engagement also decreased in week 27, which was an Easter break. The overall engagement pattern seemed to follow with the changes in LD workload over time.

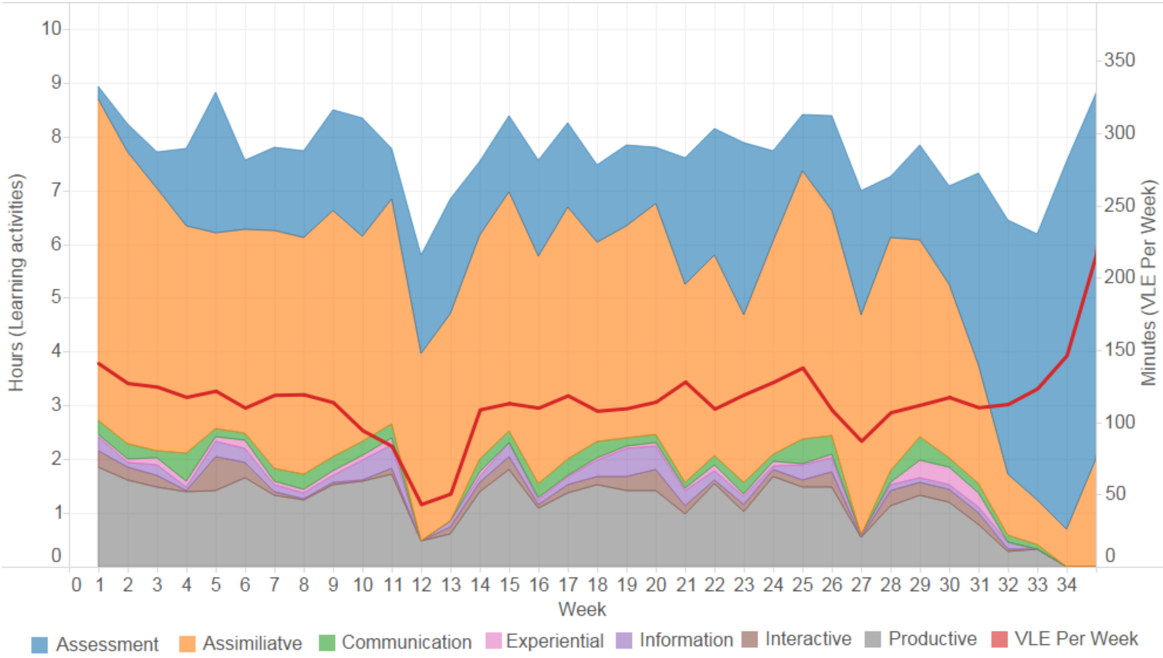

Figure 25. Longitudinal visualization of hours per week allocated for different activities in the learning design (coloured blocks) and students' average engagement in minutes per week on the VLE (red line) for 37 modules over 34 weeks

Table 28. Descriptive statistics of LD data and VLE data

	N	Minimum	Maximum	Mean	Std. Deviation
Assimilative (hrs)	1088	0.0	15.0	3.9	3.37
Information (hrs)	1088	0.0	13.0	0.2	0.72
Communication (hrs)	1088	0.0	11.0	0.2	0.72
Productive (hrs)	1088	0.0	12.5	1.3	1.72
Experiential (hrs)	1088	0.0	9.0	0.1	0.49
Interactive (hrs)	1088	0.0	19.1	0.2	0.83
Assessment (hrs)	1088	0.0	20.0	1.9	3.42
VLE per week (mins)	1088	6.5	577.0	116.3	66.35
VLE per visit (mins)	1088	2.8	51.0	22.9	8.61

N=number of data points collected from 37 modules over 34 weeks

Table 29 reported the correlation matrix between seven activity types and the time spent on VLE. The time spent on VLE per week was positively correlated with assessment (r=0.20, p<0.01), communication (r=0.27, p<0.01), and interactive activities (r=0.16, p<0.01). The average time spent per visit was positively correlated with assessment (r=0.12, p<0.01), assimilative (r=0.10, p<0.01), communication (r=0.22, p<0.01), and interactive (r=0.09, p<0.01) activities. Overall, the assessment and communication activities had the strongest correlations with time spent on VLE.

Table 29. Pearson's correlation matrix of learning design and VLE engagement at a weekly level

Variables	1	2	3	4	5	6	7	8
1. Assessment								
2. Assimilative	-.46**							
3. Communication	-.12**	.17**						
4. Information	-.12**	.08**	.17**					
5. Productive	-.29**	.16**	.13**	.17**				
6. Experiential	-.06*	.02	-.02	-.02	.00			
7. Interactive	.00	.02	.05	.01	.01	.01		
8. VLE per week	.20**	.01	.27**	.05	.01	.01	.16**	
9. VLE per visit	.12**	.10**	.22**	.04	.07*	.04	.09**	.84**

N = 37 modules (1,088 data points)

* p < .05, ** p < .01

Fixed effect models were conducted with the average time spent on VLE per week (Table 30) and per visit (Table 31) as dependent variables. For each predictor, four models were applied. First, I ran a normal OLS regression model. Second, I used the fixed-effect model to control for the unobserved heterogeneity of time. Third, I controlled for the fixed effect between modules. Finally, I controlled for the fixed effects of both time and modules. Since assimilative activities account for most of the workload, they were set as the baseline. Therefore, the following results should be interpreted relative to assimilative activities.

Table 30 shows that assessment activities were positively and significantly related to the average time spent in the VLE per week in all four models. In Models 1 and 2, the effect of assessment activities was almost the same (B = 4.98, SE = 0.57, p < 0.01 and B = 5.09, SE = 0.59, p < 0.01 respectively). The effect of assessment activities became smaller in Model 3 and Model 4 when differences between modules were taken into account. On average, an additional hour allocated for assessment activities was associated with 2.47 (SE = 0.47, p < 0.01) and 2.80 (SE = 0.47, p < 0.01) minutes increase in the average time spent on the VLE per week in Model 3 and Model 4 respectively.

Table 30. Fixed effect model of VLE engagement per week predicted by learning design activities

DV = VLE per week	Unstandardized coefficients			
	(1)	(2)	(3)	(4)
MODELS	OLS	FE_week	FE_module	FE_module_week
Assessment	4.98**	5.09**	2.47**	2.80**
	(0.57)	(0.59)	(0.47)	(0.47)
Information	2.40	3.23	-0.72	0.15
	(2.64)	(2.60)	(1.98)	(1.94)
Communication	26.29**	26.29**	16.54**	17.44**
	(2.66)	(2.62)	(2.16)	(2.11)
Productive	1.75	1.73	-1.84	-1.83
	(1.14)	(1.12)	(1.04)	(1.03)
Experiential	3.57	4.49	-2.07	-0.99
	(3.83)	(3.78)	(2.98)	(2.91)
Interactive	11.57**	11.25**	-0.33	-0.46
	(2.23)	(2.20)	(1.81)	(1.78)
Constant	95.66**	95.30**	110.6**	172.1**
	(2.91)	(2.85)	(2.46)	(10.50)
Observations	1,088	1,088	1,088	1,088
Adjusted R-squared	0.15	0.19	0.55	0.58

Standard errors in parentheses. * $p < .05$, ** $p < .01$
Baseline: assimilative

Communication activities were also positively associated with the time spent on VLE per week in all four models. For every hour increase in communication activities, the time spent on VLE per week increased by 17.44 minutes (SE = 2.11, $p<0.01$). The effect of communication activities was the strongest amongst all other learning activity types.

Interactive activities were positively correlated with time spent on VLE in Model 1 and Model 2. However, the effect of interactive activities became non-significant when the differences between modules were taken into account (Model 3 & Model 4).

Overall, LD activities explained up to 58% of the variability in student engagement in the VLE per week when controlling for the heterogeneity between modules.

In terms of time spent on the VLE per visit (Table 31), assessment, productive, and experiential activities had strong and positive effects in Models 1 and 2 but became insignificant in Models 3 and 4. Model 2 implied that an additional hour allocated for assessment activities was, on average, associated with a 0.48 minute increase in the time spent in the VLE per visit (SE = 0.07, $p < 0.01$). However, the effect became insignificant when controlling for the differences between modules. Additionally, communication activities were positively associated with time on VLE per visit in all models, while productive, experiential, and interactive activities had a significant effect in Models 1 and 2 only. Overall, by taking into account the heterogeneity within and between modules, LD was able to explain 69% of the variability in time spent on the VLE per visit (Model 4).

Table 31. Fixed effect model of VLE engagement per visit predicted by learning design activities

DV = VLE per visit	Unstandardized coefficients			
	(1)	(2)	(3)	(4)
MODELS	OLS	FE_week	FE_module	FE_module_week
Assessment	0.46**	0.48**	0.02	0.05
	(0.07)	(0.08)	(0.05)	(0.05)
Information	0.13	0.20	-0.29	-0.21
	(0.35)	(0.35)	(0.22)	(0.21)
Communication	2.76**	2.78**	0.96**	1.06**
	(0.35)	(0.35)	(0.24)	(0.23)
Productive	0.46**	0.46**	-0.17	-0.16
	(0.15)	(0.15)	(0.11)	(0.11)
Experiential	1.04*	1.09*	0.52	0.60
	(0.51)	(0.51)	(0.33)	(0.32)
Interactive	0.79**	0.72*	-0.34	-0.39
	(0.30)	(0.30)	(0.20)	(0.20)
Constant	20.56**	24.15**	21.00**	24.66**
	(0.39)	(1.37)	(0.91)	(1.18)
Observations	1,088	1,088	1,088	1,088
Adjusted R-squared	0.08	0.10	0.67	0.69

Standard errors in parentheses. * p < .05, ** p < .01 Baseline: assimilative

To further explore the relationship between LD and student engagement, I visualised two exemplary modules in Arts and in Languages (Figure 26). These two modules had a relatively similar design but the level of VLE engagement seemed to be very different. In the Arts module, we can see a peak in VLE activity in week 8-9 due to the increase in workload. The level of engagement then decreased during the Christmas breaks and sharply increase just before the Easter break in week 26. On the other hand, the level of engagement in the Language module was relatively constant throughout the module, with the exception during Christmas breaks. The level of engagement in both module slightly increased in assessment weeks, which confirmed the findings from the fixed-effect models.

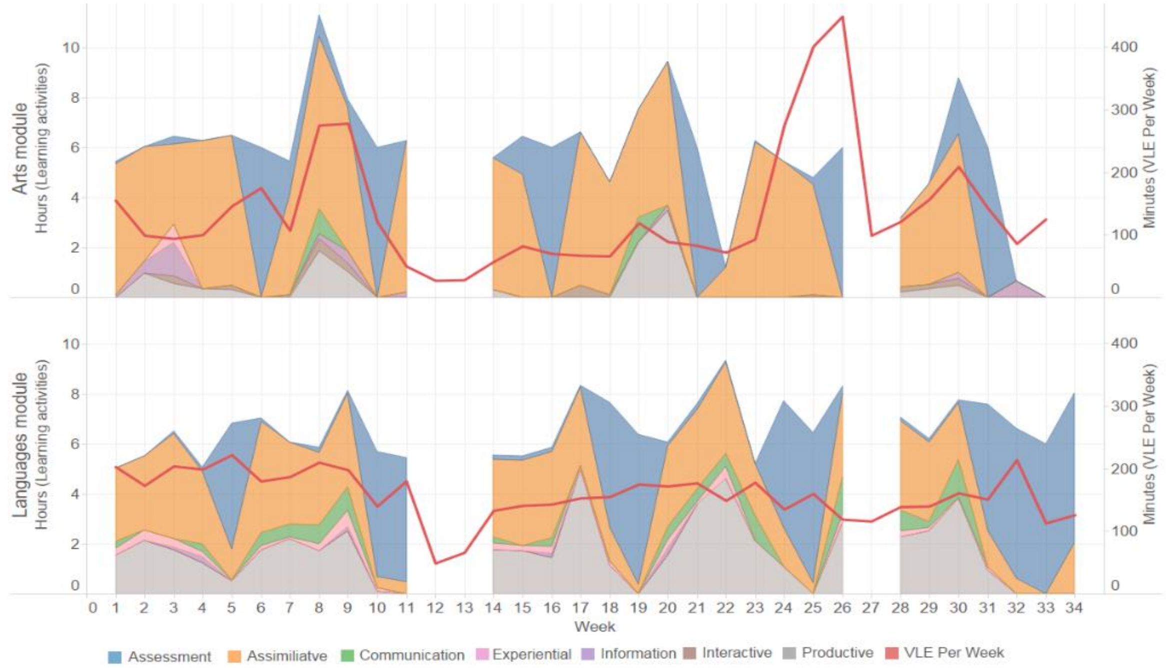

Figure 26. Learning design and VLE activity of two modules in Arts and Languages

6.3.2 Learning design, satisfaction, and pass rate

The correlational analysis in Table 32 suggested that finding information and communication activities were negatively correlated with satisfaction score. There was no statistically significant correlation between satisfaction and pass rate.

Table 32. Pearson's correlation between pass rate, satisfaction, and seven types of learning activity

	Pass rate	Satisfaction
Pass rate	1	-.139
Satisfaction	-.139	1
Assimilative	-.247	-.059
Information	.102	-.375*
Communication	.175	-.470**
Productive	-.009	-.133
Experiential	-.173	.154
Interactive	-.097	-.246
Assessment	.042	-.141

N = 37 modules, * p<0.05 ** p < 0.01

Following the correlational analysis, a multiple regression was run with satisfaction as the dependent variable and seven learning activity types as independent variables. A backward elimination process was carried out on the seven learning activity types, to determine which activity type has the strongest impact on satisfaction rate. Communication activities were negatively associated with satisfaction score in all models and explained up to 19.8% of the variation in satisfaction. For each standard deviation increase in communication, satisfaction score decreased by 0.47 standard deviation (p<0.05). The results shown in Table 33 indicated that communication activity type was the strongest predictor of satisfaction, while other six activity types did not improve the model performance (i.e. Adj-R2 increased slightly from 19.8% to 20.7% and decreased to 15.3% as more activity types were added into the model). There were no statistically significant correlations between satisfaction and the other six learning activity types.

Table 33: Multiple regression of satisfaction and seven learning activity types

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
DV = Satisfaction							
Communication	-.470*	-.602*	-.494*	-.457	-.442	-.447	-.448
Assessment		.220	.295	.261	.205	.219	.224
Information			-.220	-.211	-.275	-.250	-.237
Interactive				-.142	-.151	-.154	-.157
Assimilative					.165	.134	.121
Experiential						.091	.095
Productive							-.030
Observation	37	37	37	37	37	37	37
Adj R-squared	.198	.207	.207	.204	.198	.180	.153

Standardised coefficients. * $p < 0.05$

To further understand the relationship between communication activities and satisfaction, a scatter plot was generated (Figure 27). In line with findings from Study 1, most modules used little to no communication activities. The satisfaction score for these modules varied from 70% to 90%. However, modules with more than 5 hours of communication activities such as discussion forums, online group work started to see a downward trend in satisfaction as the number of communication activities increased.

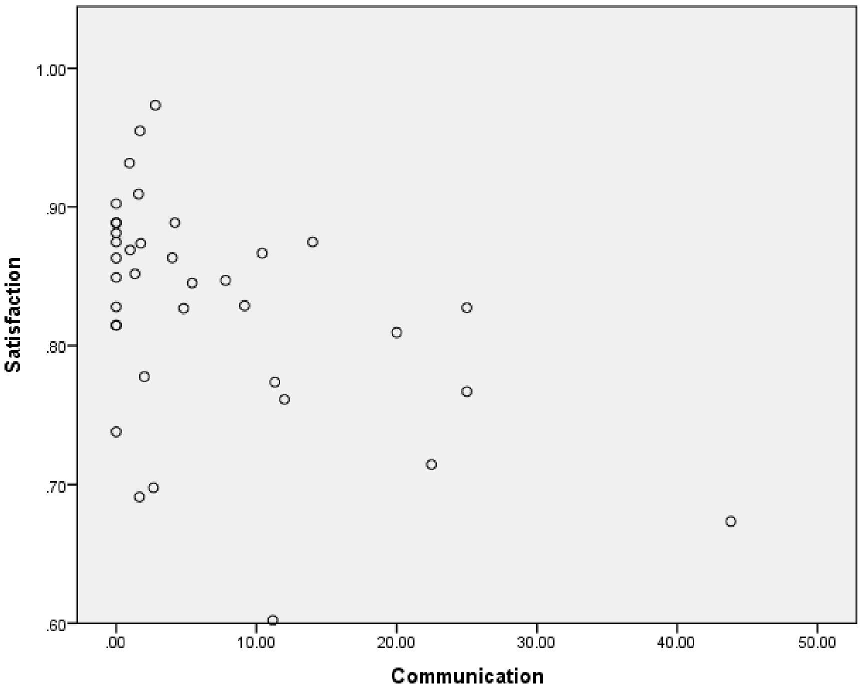

Figure 27. Scatter plot between communication activities and student satisfaction

Regarding the relationship between pass rate and LD, assimilative activities were negatively associated with the pass rate in all models (Table 34). For each standard deviation increase in assimilative activities, the pass rate decreased by 0.432 standard deviations (p<0.05). Assimilative activities explained for 9.1% of the variation in pass rate between modules.

Table 34. Multiple regression of pass rate and seven learning activity types

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
DV=Pass rate						
Assimilative	-.432*	-.492*	-.497*	-.501*	-.486*	-.498*
Information	.338	.416	.271	.272	.255	.247
Productive		-.169	-.171	-.190	-.184	-.188
Communication			.215	.242	.242	.229
Interactive				-.146	-.143	-.138
Experiential					-.046	-.042
Assessment						.039
Observation	37	37	37	37	37	37
Adj R-squared	.091	.089	.088	.082	.054	.022

Standardised coefficients. * p <0.05

While the regression model suggested a negative relation between assimilative activities and pass rate, Figure 28 showed an inconclusive pattern between the two variables. There was a large variation in pass rate 50% - 80% and this range did not seem to decrease as assimilative activities increased. The exception was the two modules with extremely high assimilative activities (300 hours) which had around 55% pass rate. This finding implies that an excessive amount of workload had a negative effect on the pass rate.

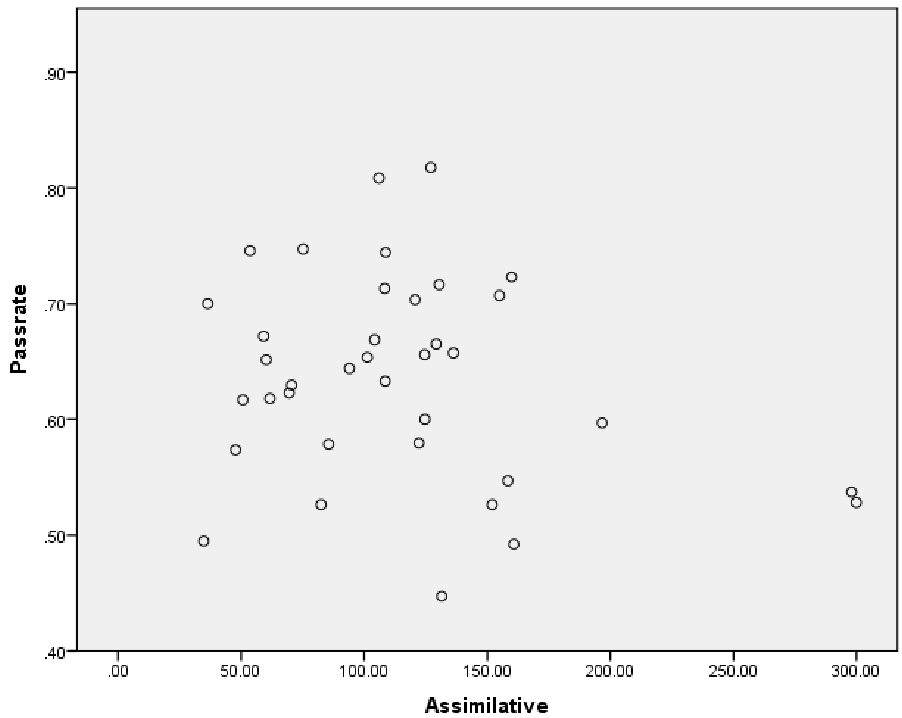

Figure 28. A scatter plot between pass rate and assimilative activities

6.4 Discussion

Study 3 has investigated the effect of LD on student engagement, satisfaction, and pass rate of 37 modules over 30 weeks. The first finding indicated that the level of engagement on VLE was positively associated with assessment and communication activities, which was in line with previous empirical results at the OU (Jordan, 2012; Rienties & Toetenel, 2016b) and in a broader education literature (Cherney et al., 2017; Holmes, 2017). The new contribution of Study 3 was the use of behavioural measurements captured from the beginning to the end of a module, as opposed to the use of self-report measures in previous studies (Cherney et al., 2017).

The engagement pattern of students found in Study 3 showed similarities with the findings of Holmes (2017), which found sharp increases in VLE engagement in weeks of assessment deadlines. One possible explanation for the positive effect of assessment on student engagement on VLE could be that students put more effort in preparation for their assessments by revisiting prior learning materials, which in turn increased their time spent on VLE. As a result, modules with a higher number of assessments would have a higher level of student engagement. Findings from Study 3 are closely linked with the findings from Study 1 and Study 2, which showed that teachers put a strong emphasis on assessment design. The implementation of single component assessment strategy at all level 1 and level 2 modules since 2018 signalled that assessment design is one of the top priorities at the OU.

While Study 3 provided empirical evidence at a macro level across a large number of modules and students, its broad categorisation of assessment perhaps did not capture the full complexities of assessment design such as the types of assessment as well as the timing of assessment (Earl et al., 2006; Hattie et al., 2007). Broadly speaking, there are three main types of assessment. These include summative assessment (i.e., assessment of learning), formative assessment (i.e., assessment for learning), and self-assessment (i.e., assessment as learning) (Earl et al., 2006; Hattie et al., 2007; Torrance, 2007). While formative assessment and self-assessments were found to positively impact student engagement and motivation (Bennett, 2011; Jordan, 2012; Panadero et al., 2018; Panadero et al., 2017; Tempelaar et al., 2013), findings on summative assessment showed mixed results (Harlen, 2006; Trotter, 2006).

The timing of engagement also plays an important role, in which continuous assessment, which is often associated with self-assessment, was found to increase student engagement more than summative assessment (Holmes, 2017; Jordan, 2012). Therefore, it is recommended for the future development of LD practices, to account for different types of assessment in their taxonomy, such as the LD pattern languages by Law et al. (2017) as described in section 2.2.2. By doing so, it would allow researchers and practitioners to validate the effectiveness of each assessment type as well as provide pedagogical advice on how to better design assessment activities.

Although assessment activities were found to be positively correlated with student engagement, the strongest predictor of student engagement was communication activities, as shown in Table 30 and Table 31. One possible explanation is that communication activities often took the form of online discussion forums, which required students to engage with the VLE. Compared to assessment activities, communications activities were unlikely to be graded. Therefore, students engaging with communications activities perhaps came from an intrinsic motivation rather than an extrinsic motivation (Ryan et al., 2000).

While communication was positively correlated with VLE engagement, it was found to have a negative effect on module satisfaction score, which is in line with Rienties and Toetenel (2016a). This finding also resonates with the teachers' perceptions of collaboration activities in Study 2, which demonstrated some tensions between what teacher's pedagogical belief and the resistance from students and tutors against collaboration activities. An explanation could be that communication activities required extra effort from students to engage with their peers through online forums, hence the time spent on VLE increased. However, students might not enjoy collaborating with others online, fearing that their grades will be influenced by their peers. Collaboration in online settings could also be frustrating to the students due to the lack of trust and rapport without face-to-face interactions. Therefore, students who dislike collaboration activities will more likely to fill in the course evaluations to express their frustrations.

Although communication activities were found to be negatively associated with satisfaction in Study 3, it is important to emphasise that this broad categorisation did not capture the complex factors associating with the design of communication and collaboration activities. For example, Salter et al. (2015) found that structured discussion forums had a higher level of engagement as well as using feedback more than an unstructured discussion forum. Other factors could influence student experience engaging in collaboration activities are group cohesion, trust, sense of community, and culture (Kreijns et al., 2003). Therefore, it is implied that teachers should carefully consider the design of online communication activities because they could have a strong (positive or negative) impact on student engagement as well as satisfaction.

Another key finding of Study 3 was the synergy between module workload and student engagement. The results showed that 69% of the variation in time spent on VLE could be explained by the seven learning activity types. The level of engagement followed the ups and downs in workload, which increased in assessment weeks and decreased during Christmas and Easter breaks. This finding implies that the way teachers design their module had a strong influence on how students learn and the amount of effort they put in. The other 31% of the variation in student engagement could be explained by differences in student characteristics, which include demographics, cognitive strategies, self-regulation strategies, the use of feedback, or learning motivations and emotions.

Since the level of engagement is heavily dependent on study workload, it is important for teachers to keep a balance and consistent amount of workload over time (Van Ameijde et al., 2016; Whitelock, Thorpe, et al., 2015). As shown in two exemplary modules, a sudden increase in workload in the Arts module led to an increase in engagement. However, students could feel overwhelmed and decreased their engagement in the long run. In comparison, the Language module had a relatively consistent workload in all weeks, which resulted in a consistent level of engagement throughout the module. This finding was also supported by the negative relation between assimilative and pass rate. Modules with extremely high workload had a low pass rate. The quantitative findings are in line with the qualitative findings from Study 2, which showed that teachers deliberately reduced study workload when redesigning their modules.

Study 3 contributes to the connection between the field of LA and LD by linking trace data of student behavioural engagement with LD representations. The novelty of Study 3 is the exploration of how student behaviours align with LD over a long period of time. The aspect of time is crucial in educational research as it allows us to unpack the complexities and dynamics of learning behaviour during the learning process. Future research is encouraged to collect and analyse data at a longitudinal level to account for the temporal changes in learning processes (Chen et al., 2018; Knight, Friend Wise, et al., 2017a). An implication for researchers working on the intersection of LA and LD is that data should be collected on the same level of specification for integration purposes. Otherwise, it is difficult to connect two data sources which were collected at different levels, for example, LD data at a module level and LA data at a daily level.

In line with recent reviews of LA (Ferguson et al., 2016; Papamitsiou et al., 2014, 2016), researchers are encouraged to look beyond “cold” LA data such as the number of clicks, time spent. Without a good understanding of the instructional context, it is difficult to interpret student behaviour and create meaningful changes in the curriculum. The implication for LA and LD research is the collection of multiple data sources for data triangulation. As shown in the three studies so far, simple visualisation of LD or description of teacher perspectives or student behaviour alone in itself may not be able to capture the nuances of complex processes of LD and student engagement. By taking into account the differences in instructional conditions between modules, Study 3 showed a considerable increase in the model performance, with an increase in R-squared from 10% to 69%.

In terms of practical implications, assessment and feedback are high on the priority list for students and educators, as they are linked to student success and to the success of a course, programme, faculty and university (Hattie et al., 2007). Some policymakers have already made moves intended to improve the effectiveness of teaching (Ferguson et al., 2016). For example, a Teaching Excellence Framework has been introduced in the UK, and it is likely that measures related to assessment will be used as key indicators. In order to explain how satisfaction and assessment activities are linked and which elements of assessment (balance of activities, spread through module material or assessment methods) have a significant impact on student outcomes, we need to combine research data and institutional data and work together in order to solve this complex puzzle.

6.5 Conclusion

In conclusion, Study 3 has provided empirical evidence at a large scale of how LD influences student engagement, satisfaction, and pass rate by combining LD data of 37 modules with trace data of 45,190 undergraduate students. The findings indicated that assessment and communication activities had a positive correlation with student time spent on VLE. However, communication activities were negatively correlated with satisfaction scores and assimilative activities were also negatively correlated with module pass rate.

There are some limitations of Study 3 that should be acknowledged. Firstly, one caveat of trace data is the problem with interpretation. Trace data might not be representative of the actual studying process, which could take place outside the learning management systems. For example, students could download a PDF offline, searching for information in another browser, or write an essay in Word. These activities are not captured by the system. Another limitation of time-on-task could be that we are not able to tell whether students were cognitively engaging with the learning activities on VLE. Behavioural engagement does not always equal cognitive engagement. Students could open a browser for a long period of time but not cognitively engaged with the learning process (i.e., checking Facebook, have a cup of tea, distracted by the external environment.

The second limitation of Study 3 is the issue of self-report satisfaction. For example, the response rate for course evaluations was low and not representative of the true population. Furthermore, there might be a sampling bias in the respondents to the surveys. For example, only students who performed really well or really poorly will be more likely to respond to the satisfaction survey.

The third limitation of Study 3 is the crude measurement of student engagement at a weekly level as there will always be a trade-off between the sample size and the level of granularity in analyses. The analysis at a weekly level omitted the individual characteristics of students such as demographics, which were explored in another study (Nguyen, Thorne, et al., 2018). There are also many hidden insights underneath the aggregated measure of time spent per week such as which materials did students access, when do they engage with these materials, are they falling behind or ahead of schedule. For this reason, Study 4 will unpack the complexity in learning behaviour in details by examining the relationship between the timing of engagement with LD and academic performance.

Chapter 7 - Study 4 The alignment between learning design and student behaviour, and its impact on academic performance [24]

Study 1 has explored the overall LD patterns through data visualisation and network analysis. This was followed by Study 2, which further unpacked the complexity of LD through a qualitative study of teacher's perspectives. Study 3 added new insights from student engagement and its relation to LD data on a large scale across 37 modules and 45,190 students over 30 weeks. These three studies so far have contributed to the holistic understanding of how teachers design their modules, and how their LD decisions influence student behaviour on a large scale. Study 4 will progress this work by examining the temporal characteristics of student engagement and its relations to LD and academic performance at an individual level.

Section 7.1 – Introduction summarises the rationale of the study, and why the temporal engagement process is being investigated, followed by the background literature, and the research questions. Section 7.2 – Methods describes an overview of the specific methods in Study 4 including information about the setting, participants, instruments and data analysis approach. Section 7.3 – Results presents the findings in relation to each research question. Section 7.4 – Discussion relates the implications for research and practitioners. Section 7.5 – Conclusion discusses some limitations and future research directions.

7.1 Introduction

Previous chapters have demonstrated the importance of linking LA with LD (Lockyer et al., 2013; Mor et al., 2015; Persico et al., 2015). Although substantial progress has been made within the LAK community to link how teachers' LD decisions with what students are doing (Bakharia et al., 2016; Lockyer et al., 2013; Nguyen, Rienties, et al., 2017b; Rienties & Toetenel, 2016b; Rienties et al., 2015), one major methodological challenge that is often ignored is the granularity of analysis between LD and LA. Most LD activities are conceptualised at a course level, or at a weekly level (Nguyen, Rienties, Toetenel, et al., 2017). However, the actual behaviour of students occurs on a much finer, hours by hour or even second by the second level. It is inevitable that this will lead to discrepancies between intended and actual observed learning behaviours. In other words, there remains a paucity of empirical evidence on the magnitude and temporal characteristics of

[24] The empirical investigations undertaken for this chapter have now published as:

Nguyen, Q., Huptych, M., & Rienties, B. (2018). *Linking students' timing of engagement to learning design and academic performance* **(best full paper award)**. In proceedings of the 8th International Learning Analytics & Knowledge Conference, Sydney, Australia. 141-150

Nguyen, Q., Huptych, M., & Rienties, B. (2018). Using Temporal Analytics to Detect Inconsistencies between Learning Design and Student Behaviours. *Journal of Learning Analytics, 5*(3), 120-135.

behavioural differences in online environments, and how differences in behavioural patterns of students might vary across different levels of academic performance.

Time management in learning

Time management has been well-documented and empirically tested in educational literature as one of the key predictors in academic performance (Broadbent et al., 2015; Claessens et al., 2007; Kim et al., 2015). Time management in educational settings describes students' effort to effectively make use of their time to achieve certain educational goals within a given period of time (Britton et al., 1991; Macan et al., 1990). Time management can be viewed as a part of the self-regulated learning framework in which it reflects the planning and goal setting process of learning when working on a task (Winne et al., 1998). A recent systematic review of 12 studies by Broadbent et al. (2015) suggested that the strategies of time management, metacognition, effort regulation, and critical thinking were positively correlated with academic performance in an online setting. Numerous studies have confirmed that students who manage their time ineffectively (e.g., procrastinating, cramming for an exam) performed poorly on academic tasks (Cerezo et al., 2017; Kim et al., 2015; Whitelock, Thorpe, et al., 2015). For example, Wolters et al. (2017) found that time management is a key aspect of self-regulated learning and can extend our understanding in how students procrastinate their academic work.

Although the subject of time management has been extensively studied in the past, there remain three gaps in the literature. Firstly, many studies on time management have mainly relied on self-reported measures (Claessens et al., 2007), such as the time management behaviour scale (TMBS) (Macan et al., 1990), the time structure questionnaire (TSQ) (Bond et al., 1988), and the time management questionnaire (TMQ) (Britton et al., 1991). As a result, some key aspects of time management (what, when, and for how long students engage) have not been fully understood. Secondly, several studies have used classroom observational measures of academic engagement, such as scoring systems according to a coding scheme, or an observer recording the time interval of a pre-defined category of behaviours. However, such classroom observations are time-consuming, limited in scale (i.e., online learning with a large cohort), and subject to observers' bias and possibly errors if poorly trained. Thirdly, the role of learning design in how students manage their time has received limited attention. From a self-regulated learning perspective, the conditions in which learning take place influence how students operate (e.g., time management). Therefore, it is crucial to understand how teachers design their course and its influence on what, when, and for how long students studied.

Temporal analytics

Learning occurs over time. The concept of time in educational studies can take many forms such as longitudinal study over years, learning gains across modules, lessons within a course, activities within a lesson, and how students navigate within each activity. Advances in technology allow researchers to capture fine-grained digital footprints of student behaviours (what, when, and for how long students study). Learning analytics as a field has been progressing towards temporal analysis both conceptually and methodologically (Chen et al., 2018; Knight, Friend Wise, et al., 2017b). As highlighted in the two recent special issues of the Journal of Learning Analytics, there remain some discrepancies between how learning constructs are conceptualised with respect to time and how they are represented in data (Chen et al., 2018; Knight, Friend Wise, et al., 2017b). Research in time management, by nature, is closely coupled with temporal analytics. For example, Tabuenca et al. (2015) used a combination of the Validity and Reliability of Time Management Questionnaire (VRTMQ), Online Self-Regulated Learning Questionnaire (OSLQ), and a mobile track tool. The authors found positive effects of tracking time on time management skills. In a similar direction, Manso-Vázquez et al. (2016) proposed a comprehensive solution to use SRL criteria to select and display data focusing on time management.

Another construct that closely relates to time management and temporal analytics is engagement. Time management can be represented by what, when, and for how long students engage in learning activities. While engagement is a frequently used term by both researcher and practitioners in education, the conceptualization of engagement and its measurements has not reached a consensus. Engagement is a multi-dimensional construct ranging from behavioural engagement, emotional engagement, cognitive engagement, and agentic engagement (Azevedo, 2015; D'Mello et al., 2017; Gobert et al., 2015; Greene, 2015; Miller, 2015; Sinatra et al., 2015). As highlighted in the special issue of Educational Psychologist, Sinatra et al. (2015) recommended that engagement should be considered on a continuum from person-centred to context-centred orientation. Based on this continuum, temporal analytics is placed towards the person-oriented direction. At this end of the continuum, measurements of engagement consist of trace data, or physiological indicators such as eye-tracking, heart rates, etc.

Chen et al. (2018) discussed two features of temporal analytics. The first relates to the passage of time (how long, how often students engage). The second refers to the sequential order in which these activities take place (Molenaar et al., 2014). Both features are influenced by students' instructional conditions (i.e., learning design). Teachers often allocate a certain amount of time to each learning activity and organize a series of learning activities in an order that they find optimal. For example, students are guided to read chapter 1 in one hour, following by some open-ended questions for 20 minutes, and then join the discussion forums for 10 minutes to discuss what they have learnt with peers. As a result, LD is crucial to temporal analytics as it provides a reference point to interpret and develop measures for engagement.

Research questions

When teachers design for learning, they often estimate the workload of each activity and the corresponding time period for each activity (e.g., take 3 hours to read chapter 2 in week 2). LD is often embedded in the course syllabus and acts as a guideline for students to self-regulate their learning process (Biggs et al., 2007; Dalziel, 2015; van Merriënboer et al., 2002). However, students as agents consciously, and perhaps opportunistically, make decisions on what, how, and when to engage in a particular range of learning activities (Winne, 2017). While teachers might think that a student will read chapter 2 in week 2, perhaps some students are already pre-reading materials from week 4, while other students may not have watched the introduction video of week 1. Therefore, by having a better understanding of how much time students spent on respective learning materials and, more importantly for Study 4, when in time they studied these learning materials, this may enhance our intertemporal understanding of how students make complex study decisions.

While previous research has shown a strong correlation between the LD and student behaviour on the VLE (Nguyen, Rienties, et al., 2017b; Nguyen, Rienties, Toetenel, et al., 2017; Rienties & Toetenel, 2016b), the collapse of the time spent on all activities under a module or a week remains a problem for interpretation. For example, not all activities on the VLE are relevant and comparable to the LD (e.g., personal site, library service, accessibility service). Secondly, the timing of studying has not been fully understood (e.g., studying all materials of week 2 on day 8, 9, or 13). For instance, students could study the learning materials before or after the assigned week. Therefore, Study 4 takes a further step to investigate the time spent on each individual activity and when the students engage in these activities.

RQ4.1: How does students' timing of engagement align with learning design?

Furthermore, many LA studies have indicated that trace behaviours are significantly related to their academic performance (Macfadyen et al., 2010; Tempelaar et al., 2015). In addition, extensive research has shown that the ability to plan study time and tasks (time management) was found to be a significant predictor of academic performance (Broadbent et al., 2015; Häfner et al., 2014). It has been widely acknowledged that students with better learning strategies and self-regulation strategies are more on track with managing their study choices, while students who end up behind the course schedule might struggle to effectively perform over time (Järvelä et al., 2013; Vermunt et al., 2004). Thus, Study 4 hypothesizes that high-performing students spend more time studying the learning materials in advance, or in line with the LD, while low-performing LD students spend more time in catching up in their study.

RQ4.2: How does students' timing of engagement relate to academic performance?

By understanding the relationship between student engagement and academic performance, teachers could provide appropriate support to students who were struggling with catching up with the module activities.

7.2 Methods

7.2.1 Setting and Participants

Study 4 took place at the Open University UK. The context of the study is a level 2 module, 30 credits, which corresponds to the 2nd year course at normal face-to-face universities, focusing on Environmental Studies. Firstly, this module was selected because of the availability of trace data at a fine-grained level. These included over a million records of URLs which contained all learning materials and learning activities that students engaged with, together with student id and a timestamp of when each student accessed these materials/activities. This type of fine-grained data plays a critical role to answer RQ4.1 and RQ4.2 because they allowed me to compute new engagement metrics of the individual student based on both the duration and the timing of their engagement. These new metrics will be described in detail in section 7.2.2. Compared to Study 1 and Study 3, which used an aggregated measurement of student engagement at a weekly level, Study 4 aims to analyse student engagement at a much finer granularity.

The second reason for choosing this module was because of its LD. Given RQ4.1 and RQ4.2, which focused on comparing teachers' assumptions and actual student behaviour, it is crucial to ensure an accurate representation of the actual learning activities. Therefore, this module was selected because the majority of its learning activities took place online on the VLE, in this case, a Moodle platform. This allowed us to capture a more reliable representation of actual online learning behaviour than other modules at the OU, whereby learning activities could take place outside of the VLE (e.g., printed materials, blended learning) (Toetenel et al., 2016a). A web-scraping process was carried out to extract the URL of each learning activity, together with a deadline in which the learning activity should be finished. For example, if activity A was assigned in week 1, then its deadline will be the first Monday of week 2. These data were then combined with student trace data to determine whether a student was engaging before or after the deadline. More details are provided in section 7.2.2.

Study 4 collected data from 268 and 267 registered students in two consecutive semesters (Fall 2015 and Fall 2016 respectively) for replication purposes. However, since the research questions focus on exploring the study patterns across different groups of performance (based on final scores), the analysis in Study 4 only took into account students who had completed the course. Thus, the analysis was conducted on 182 and 198 students in Fall 2015 and Fall 2016 respectively.

Regarding demographics, there were more male (62%) than female students. The majority of the students were from the UK (92%) and of white ethnicity (88%). In contrast with typical university student profiles, only 14% of the students were under 25 years old, while 44% were from 26 to 35, 27% from 36 to 45, 10% were from 46 to 55, and 5% were over 56. Most students had a full-time job (64%), or a part-time job (16%) while taking the course. The prior educational qualification of students in this module was also diverse, with 29% less than A levels, 39% with A-levels or equivalent, and 28% with a higher education qualification. The demographics figures stayed consistently between 2015 and 2016 semesters.

7.2.2 Instruments

Learning design mapping

Similar to Study 1, 2, and 3, Study 4 collected LD data from the Activity Planner profile tool based on the OULDI learning activity taxonomy. The seven types of learning activity (assimilative, productive, communication, experiential, interactive, finding information, and assessments) were measured in terms of the duration (in hours) that was recommended for each type of activity in a particular week (Figure 29). The purpose of the recommended time spent is to support students in time management in self-regulated learning. The number of credits to be gained determined the total workload of each module, which is the sum of the time allocated for all seven types of learning activity. Each credit is associated with 10 hours of study (so 30 credits = 300 h and 60 credits = 600 h). However, the actual workload can be different and depends on each module's implementation, student characteristics, and student abilities.

Within this document you last viewed: What are systems?

Block 1 Part 1: Reflecting on domestic environmental management

Introduction

In this part, you will begin reflecting upon domestic environmental management. This part will describe further the importance of the domestic context, and give you resources to enable you to make sense of your own domestic environmental management. You will do this through data collection and the introduction of two systems diagram types – systems maps and rich pictures. You will also learn more about the nature of systems and boundaries, and the concept of ecological literacy.

The estimated study time for this week is 10 hours.

Below I have outlined the main activities for this week and the recommended time to be spent studying them.

Component	Recommended time spent
Activity 1.1: perspectives on the nature of systems	20 minutes
Activity 1.2: ecological literacy	30 minutes
Activity 1.3: calculating energy and water usage	60 minutes
Activity 1.4: drawing a rich picture	45 minutes
Activity 1.5: drawing a systems map	45 minutes
Activity 1.6: reflecting on boundary choices	20 minutes

Figure 29. Example of time allocation for each learning activity

In this target module (Figure 30), there were five different types of learning activity, whereby three types of activities (assimilative, productive, assessment) accounted for 91.64% of the total workload, which was included for comparison purposes. This was due to the difficulty in capturing the actual time spent on finding and handling activities since students could go outside of the VLE for searching information (Knight, Rienties, et al., 2017). At the same time, measuring time spent on communication was troublesome, as the compulsory communication activities designed to support certain tasks, and the optional communication activities (e.g., social, café talk) were collapsed under one discussion forum.

On average, students in this module were expected to spend 7 hours each week for assimilative, productive, and assessment activities combined. Assimilative activities were allocated on average of 4.05 hours per week (SD=3.32), followed by productive activities (M=1.47, SD=1.24), and assessment activities (M=1.49, SD=2.88). Even though the LD remained almost the same between the two semesters, there were two small changes. First, there were only two tutor-marked assignments (TMAs) in 2016 instead of three assignments in 2015. Second, the study materials of week 12 and 13 were combined in 2015, while they were separated for each week in 2016.

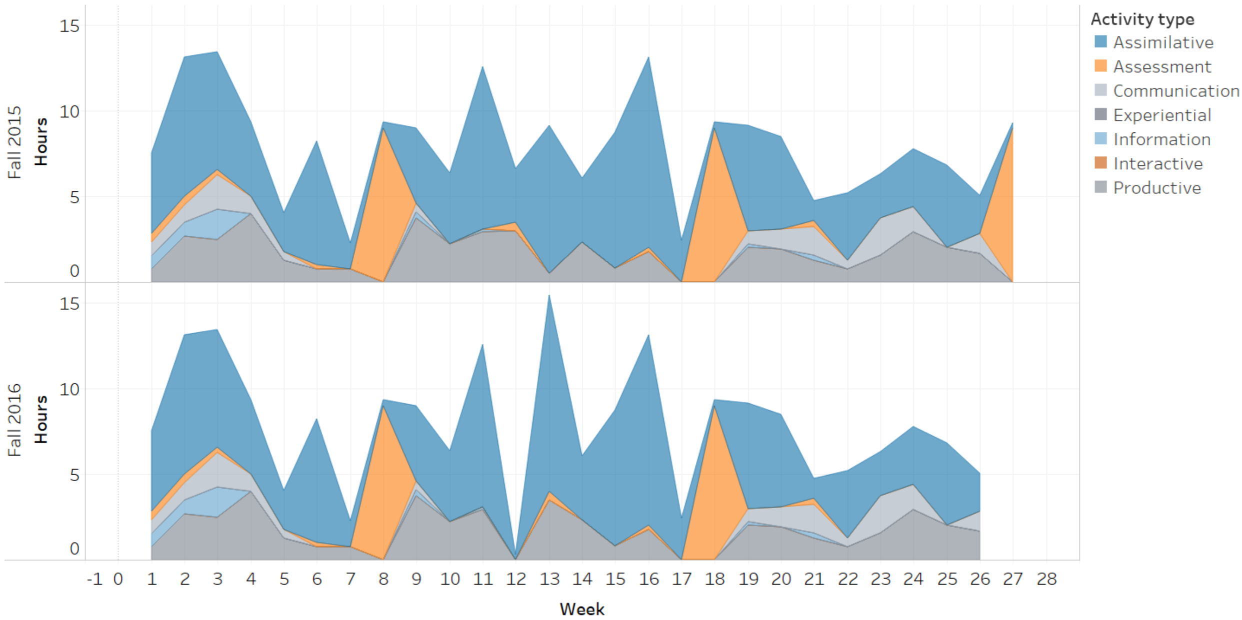

Figure 30. Learning design over two semesters

VLE engagement

The second dataset consisted of clickstream data of individual students from the VLE and was retrieved using SAS Enterprise 9.4. The data were captured from four weeks before the start of the module until four weeks after the end of the module. Learning activities were planned for over 30 weeks. Data were gathered in two semesters (Fall 2015 and Fall 2016) in order to validate the findings from two independent implementations. First, the student behaviour record includes all students' VLE activity. In other words, 'the time spent ' is determined as the time between any two clicks of a student, regardless of a course and a type of the VLE activity. Further, not each click can be associated with studying time; for instance, there are clicks related to downloading of some material. We have this information about an action type which is connected with the click. Thus, I can determinate that a click with the connected action 'download' was not included in the spent time of student in the analysis. Nonetheless, I can assume that the time of a click with the connected action ‘view’ is associated with the time of learning of a study material for which the click is logged.

To compare the LD with the actual student behaviour, time spent on task was calculated as the duration between clicks. As pointed out by previous research (Kovanovic et al., 2016), this metric could be problematic due to (1) the inability to differentiate between active time and non-active time (students leave the respective web page open and go for a coffee), and (2) the last click of the day is followed by a click next day), which makes the duration excessively long. Any attempt to set an arbitrary cut-off value would pose a threat in underestimating or overestimating of the actual engagement time.

Taking into account the context and LD of a module could produce a more informed cut-off value. Ideally, this cut-off value should be tailored to the design and context of each individual activity. For example, the cut-off value should be different between a 20 minutes activity and a 1-hour activity. While Study 4 does not fully address the aforementioned problems, it leveraged the design of learning activities based on discussion between researchers and designers to set a cut-off value at 1 hour for all activity (e.g., any activity goes beyond 1 hour will be set as 1 hour).

Since my research question aims at examining to what extent students’ timing of engagement aligns with teacher LD, two types of study patterns were computed which capture how much time a student spent on studying a particular study material:

- in advance – material x assigned to week t was studied during or before week t
- catching up and revise – material x assigned to week t was studied after week t

For example, Figure 31 visualised the time spent on week 8’s learning activities. Evidently, students spent the highest amount of time engaging in week 8’s activities in week 8. However, students also spent a small amount of time studying week 8’s materials before and after week 8 (week 6-10).

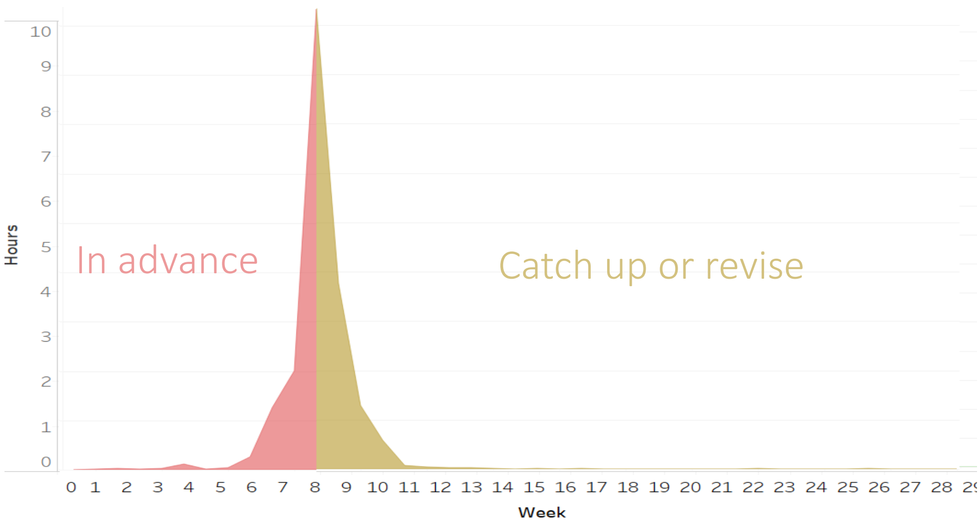

Figure 31. Time spent on week 8's learning activities

In the second research question, I am interested in understanding how these two patterns of learning behaviours varied across three different groups of performance, which was measured as the average of all tutor-marked assignments (TMAs) and final exams:

- Failed (average score < 40% or final exam score < 40%),
- Passed (40% < average score < 75% and final exam score >= 40%), and
- Excellent (average score > 75% and final exam score >= 40%).

This categorization builds on previous predictive analytics research (Kuzilek et al., 2015), which estimated these three categorizations of students across large numbers of students. Of all students completed who the course, there were 52 failed students (M=21.2 %, SD=16.7 %), 106 passed students (M=63.6 %, SD=7.5 %), and 31 excellent students (M=79.5 %, SD=3.7%) in 2015, and 50 failed students (M=25.4 % SD=15.9), 119 passed students (M=63.1 %, SD=8.0 %), and 29 excellent students (M=79.7 %, SD=3.2 %) in 2016. We also controlled for the initial level of performance, which was calculated as the average scores of all courses that a student took prior to this course.

7.2.3 Data analysis

Visualizations

To address the first research question, I visualised actual study patterns against the LD over 30 weeks. Next, I visualised the study patterns for respective individual study materials across excellent, passed, and failed group. The visualizations were done using Jupyter Notebook and Tableau.

Mixed-effect model

In order to compare study patterns across three groups of performance over time, I used a multilevel modelling (MLM) (or mixed-effect modelling) approach (week t is nested within student i). Compared to the traditional repeated measure ANOVA approach, MLM has less stringent assumptions (homoscedasticity, compound symmetry, and sphericity), allows for missing data, tolerates differently spaced waves of data (e.g., due to Christmas breaks, Easter breaks), accounts for autocorrelation of residuals, and allows for nonlinear relations (Quené et al., 2004). First, I started with a random intercept model (weeks are nested within students) as the baseline (not reported here). To address RQ4.2, I composed two models. The first model (M1) focused on comparing three groups of performance (baseline = passed students) over time with the time spent on studying 'in advance' and 'catching up' as the outcomes.

$$\log(1 + y_{ti}) = \beta_{0i} + \beta_{1i}week_t + \beta_2 Excellent_i + \beta_3 Fail_i + e_{ti}$$

$$\beta_{0i} = \beta_0 + \mu_i$$

$$\beta_{1i} = \beta_1 + \mu_i$$

The second model (M2) took into account individual student characteristics (age, gender, education, occupation) and time-variant characteristics (the designs of assimilative, productive, assessment activities). However, since demographics did not improve the overall fit of the model (based on the likelihood ratio test) (Quené et al., 2004), they were excluded in the end.

$$\log(1 + y_{ti}) = \beta_{0i} + \beta_{1i} week_t + \beta_2 Excellent_i + \beta_3 Fail_i + \beta_4 Assimilative_t + \beta_5 Productive_t + \beta_6 Assessment_t + e_{ti}$$

$$\beta_{0i} = \beta_0 + \mu_i$$

$$\beta_{1i} = \beta_1 + \mu_i$$

Where outcome y was in advance time or catchup time. Week t was nested within individual i

The analysis was done using the lme4 package (Bates et al., 2015) in R v.3.3.2 statistical package. Given the moderate sample size and balanced data, p-values were calculated using Type II Wald chi-square tests. A log transformation on the dependent variables (in advance time, and catchup time) was performed after examining the normality of the residuals. The assumptions of homoscedasticity, multicollinearity, residuals auto-correlation, and non-linearity were checked in all models which indicated there were no severe violations of these assumptions.

7.3 Results

7.3.1 Learning design and timing of engagement

Figure 32 illustrates the total time that students spent on study materials in the assigned week against the time recommended from the LD for the same study materials. Compared to the LD (grey line), students in both semesters on average spent much less time studying in the VLE per week (M=3.59, SD=5.29 for 2015; M=3.17, SD=4.55 for 2016). In line with previous work (Nguyen, Rienties, et al., 2017b; Nguyen, Rienties, Toetenel, et al., 2017), the actual study patterns seemed to follow the same trends in the LD. Overall, students in both semesters spent on average more time studying the materials after the assigned week (catching up and revise) (M=2.14, SD=4.05 for 2015; M=1.91, SD=3.48 for 2016) than before the assigned week (in advance) (M=1.45, SD=3.09 for 2015; M=1.26, SD=2.82 for 2016), except for studying the materials in week 8, week 18, and week 27 (in Fall 2015), which was a tutor-marked assignment (TMA).

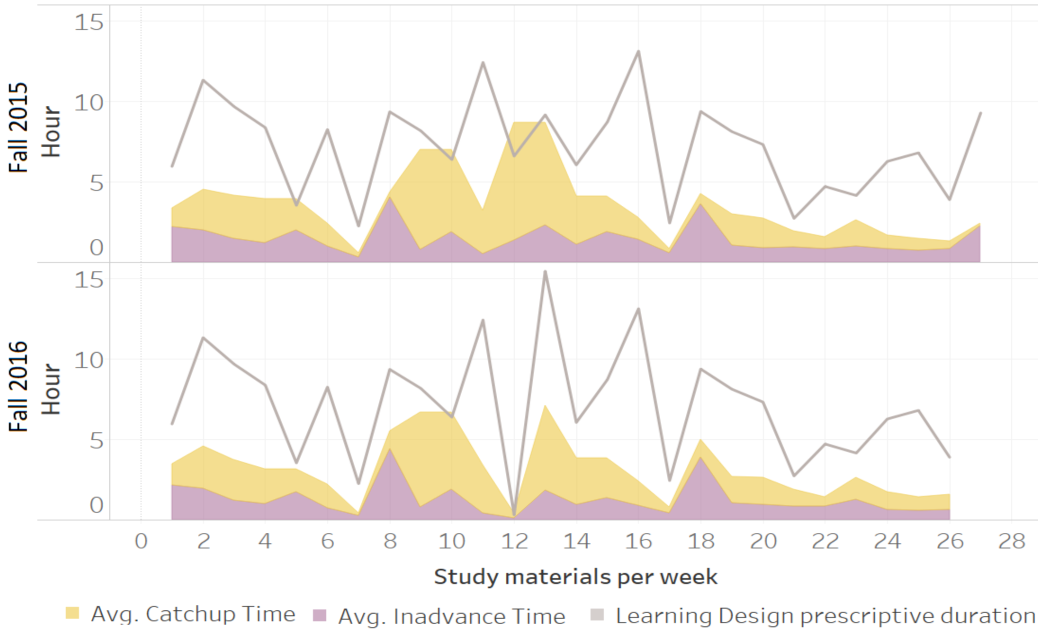

Figure 32. Time spent on study materials per week against the time recommended by teachers

A closer look at the study patterns across the three different groups of performance (failed, passed, and excellent) was shown in Figure 33 & Figure 34. Overall, given the same study materials, the passed and the excellent group of students spent more time on studying in advance and catch up than the failed students in both semesters (Figure 33 & Figure 34). In Fall 2015, passed and excellent students spent on average each week 1.81 hours (SD=3.43), and 2.3 hours (SD=3.52) on studying in advance, compared to failed students with an average of 0.22 hours (SD=1.05). Similar trends in the time studying in advance across the three groups was also presented in Fall 2016. In Fall 2015, passed and excellent students followed a similar pattern studying in advance. However, in Fall 2016 passed and failed students portrayed a similar pattern for all study materials from week 1 to week 12. From week 13 onwards, passed students spent more time studying in advance than failed students. A lot of time was spent on studying in advance in week 8, 18, and 27 (for Fall 2015) because of the respective assessments (TMAs) in these weeks (Figure 33).

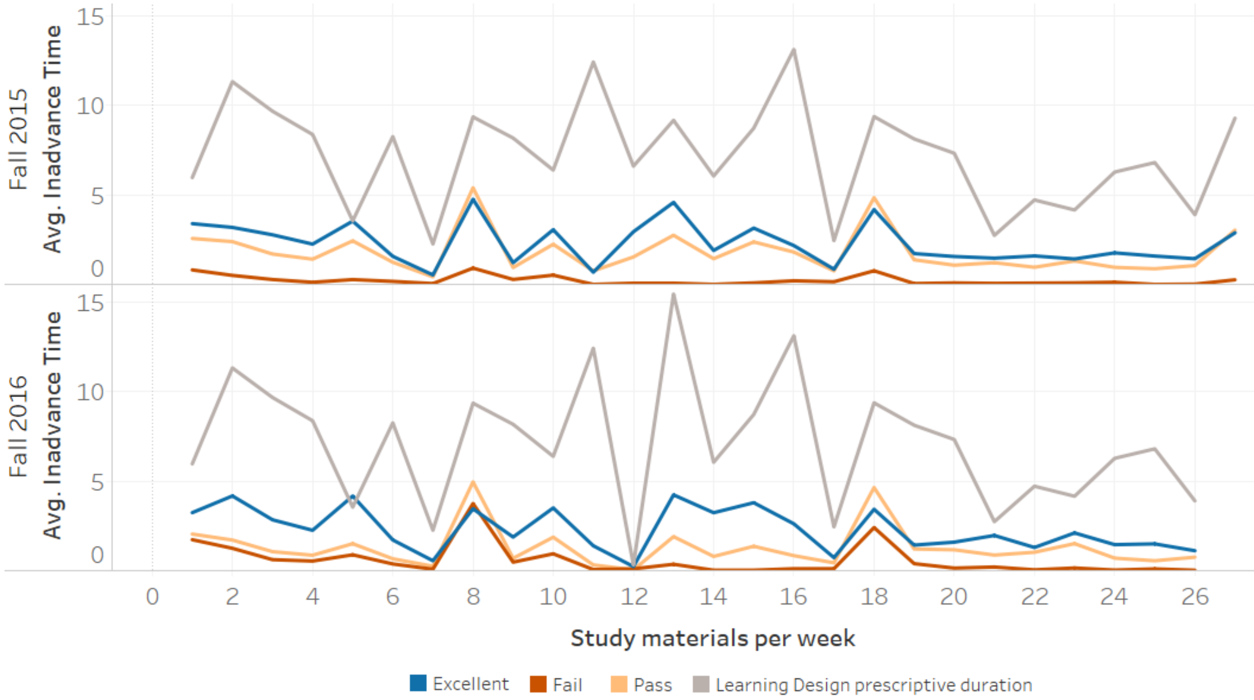

Figure 33. Number of hours spent on studying in advance

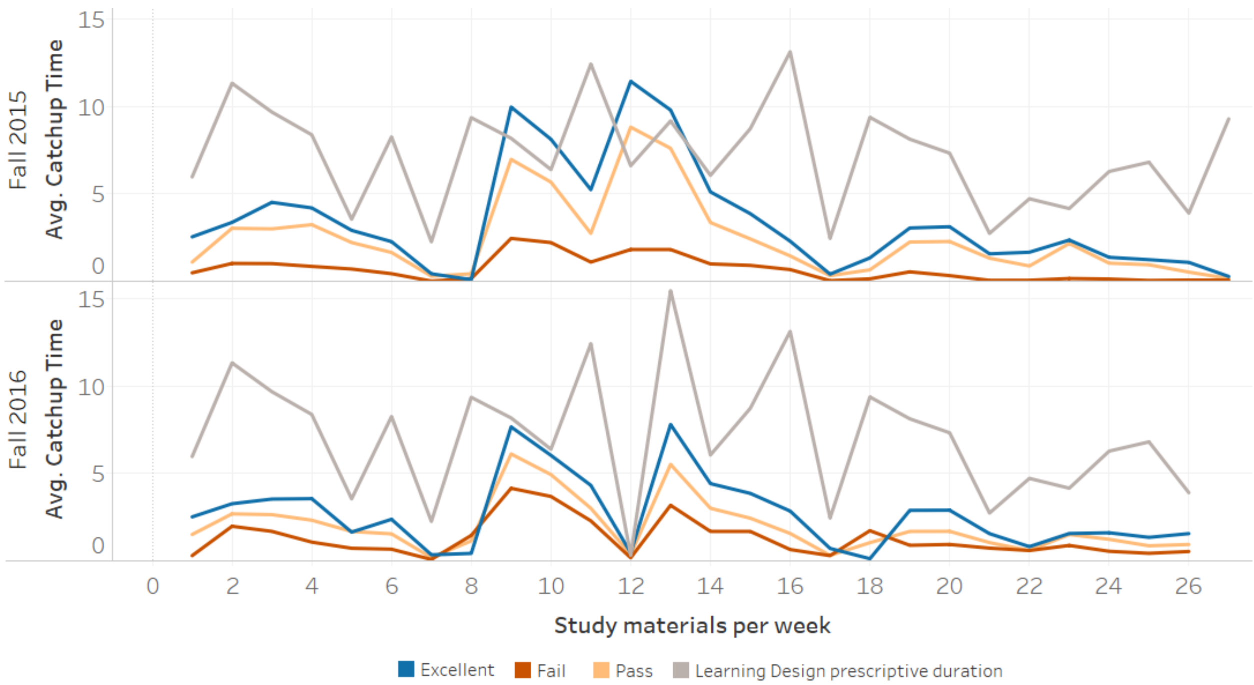

Figure 34. Number of hours spent on studying catching up and revising

Two study materials in weeks 9-10 (block 2.1) and weeks 12-13 (block 2.3) represented red-flags of overwhelming workloads since they were associated with an increase in both studying in advance and catch up time (Figure 33 & Figure 34). In Fall 2015, the passed and excellent students spent much more time to catch up on both of the materials, while the gap was smaller in 2016.

While excellent and passed students consistently spent more time studying both in advance and catch up than failed students, the relative frequencies revealed a different picture. In both semesters, all three groups of students spent a similar percentage of their time studying in advance in weeks which had a TMA (week 8, 18, 27). However, in Fall 2015 failed students spent a higher proportion of their time on catching up activities (61% on average) than passed (56%) and excellent students (55%) in almost all weeks (Figure 35).

In Fall 2016, the three groups shared a similar percentage of study time on catching up from week 1 to week 12. After week 12, failed students spent on average much higher proportion of their time on catching up activities compared to passed and excellent students. Towards the end of the course, the gap between failed and passed/excellent students increased considerably (Figure 35).

In other words, the initial visualisations of Study 4's results indicated that student engagement on VLE was lower than the suggested time spent in LD. High-performing students, who achieve a pass or excellent grade shared similar patterns of engagement. However, low-performing students spent the least amount of time on VLE and the highest proportion of their studying time on catching up and revising activities. While these visualisations were useful for exploring the overall trends, the followed-up statistical modelling will provide a robust conclusion and quantify the effect of timing of engagement on academic performance.

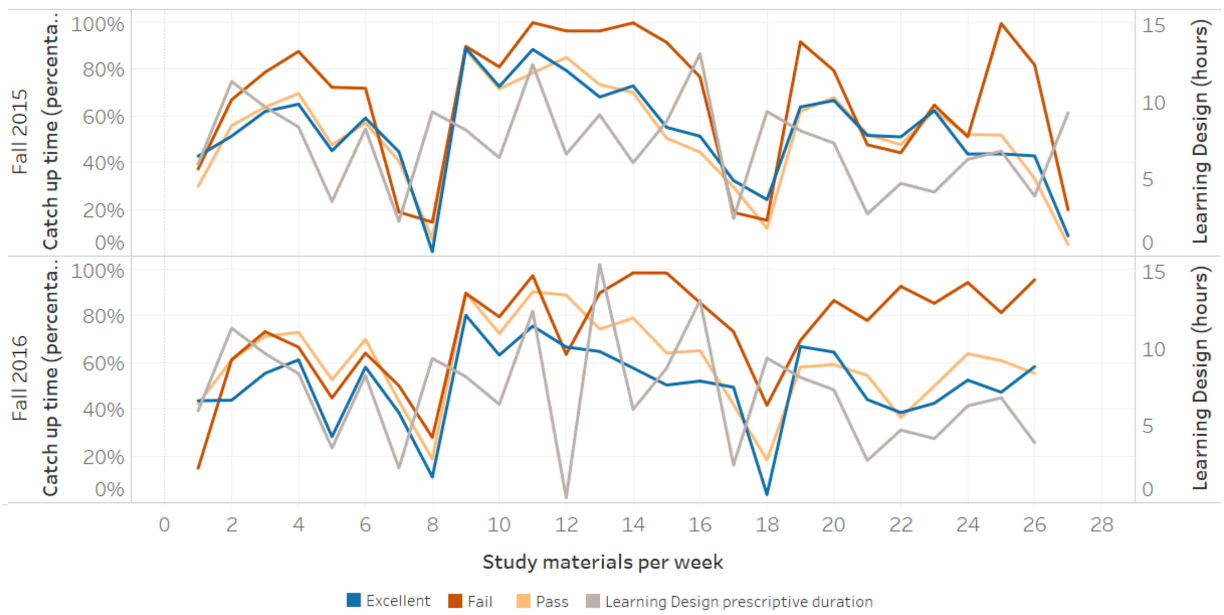

Figure 35. Percentage of time spent on studying catching up

7.3.2 Academic performance and timing of engagement

Compared to passed students, failed students spent significantly less time on studying in advance (B= -0.23, SE = 0.03, p<0.001) in 2015, while there was no statistically significant difference with excellent students (Table 35). A similar pattern was observed in 2016 for failed students (B= -0.14, SE = 0.03, p<0.001) while excellent students spent significantly more time on studying in advance (B = 0.12, SE = 0.03, p<0.001) (Table 35). Since I performed a log-transformation with the dependent variable, the coefficients should be exponentiated for meaningful interpretations. In other words, compared to passed students, the time spent on studying in advance will be 13.06% lower for failed students, and 12.75% higher for excellent students. After adding the LD (Model 2), the relations between different groups of performance and the time spent on studying in advance remained the same. In 2015, the higher the time designed for assimilative and assessment activities, the higher the time spent on studying in advance. A negative relation was found between productive activities and the time spent on studying in advance. In 2016, the effects of assimilative and productive on the time spent on studying in advance were no longer significant. In other words, for each hour increase in assessment activities, there is a 3-4% increase in the time spent on studying in advance.

Table 35. Mixed effect model of time spent on studying in advance

	Fall 2015			Fall 2016		
	Model 1 B(SE)	Model 2 B(SE)	Model 3 B(SE)	Model 1 B(SE)	Model 2 B(SE)	Model 3 B(SE)
Fixed						
Intercept	.30(.02)	.30(.03)	.02(.09)	.26(.02)	.20(.02)	-.01(.08)
Week	-.00(.00)**	-.00(.00)***	-.00(.00)***	-.00(.00)***	-.00(.00)***	-.00(.00)***
Fail	-.23(.03)***	-.23(.03)***	-.19(.03)***	-.14(.03)***	-.14(.03)***	-.11(.03)***
Excellent	.07(.04)	.07(.04)	.04(.04)	.12(.03)***	.12(.03)***	.11(.04)***
Assimilative		.00(.00)*	.00(.00)*		.00(.00)	.00(.00)
Productive		-.02(.00)***	-.02(.00)***		.00(.00)	.00(.00)
Assessment		.03(.00)***	.03(.00)***		.04(.00)***	.04(.00)***
Initial Level			.00(.00)***			.00(.00)***
Random						
Students	.06(.24)	.06(.24)	.05(.23)	.05(.22)	.05(.23)	.05(.22)
Week	.00(.01)	.00(.01)	.00(.01)	.00(.01)	.00(.01)	.00(.01)
LogLik	-470.8	-198.5	-173.4	-550.2	-122.1	-143.3
Obs	5103	5103	4968	5148	5148	4966
Students	189	189	184	198	198	191

*p<0.05; **p<0.01; ***p<0.001

Log-transformation on in advance time. Baseline = Passed students

Standard errors in parentheses for Fixed estimators

Standard deviation in parentheses for Random estimators

In line with the previous visualization (Figure 35), compared to passed students, failed students spent significantly less time on studying catching up (B= -0.20, SE = 0.03, p<0.001), while excellent students spent significantly more time (B= 0.08, SE = 0.03, p<0.001) (Table 36). In other words, compared to the passed students, the time spent on catching up study was 22.14% lower for the failed students, and 8.33% higher for the excellent students. This catching-up could also be regarded as repeating particular learning activities, whereby a vast body of cognitive learning research has found that learning requires repetition. In a similar trend, in Fall 2016 compared to passed students, the time spent on catching up study was 12.75% lower for failed students, and 10.52% higher for excellent students. All three types of learning activity had a significant relation with time spent on catching up. While the effect of assimilative and assessment activities was relatively small, one hour increase in productive activities was associated with a 7.25% increase in the time spent on catching up.

Table 36. Mixed effect model of time spent on studying catching up and revise

	Fall 2015			Fall 2016		
	Model 1 B(SE)	Model 2 B(SE)	Model 3 B(SE)	Model 1 B(SE)	Model 2 B(SE)	Model 3 B(SE)
Fixed						
Intercept	.46(.02)	.23(.03)	.09(.08)	.40(.02)	.15(.02)	.02(.08)
Week	-.01(.00)***	-.00(.00)***	-.00(.00)***	-.01(.00)***	-.00(.00)***	-.00(.00)***
Fail	-.20(.03)***	-.20(.03)***	-.18(.03)***	-.12(.03)***	-.12(.03)***	-.11(.03)***
Excellent	.08(.03)**	.08(.03)**	.06(.03)	.10(.03)**	.10(.03)**	.09(.04)*
Assimilative		.01(.00)***	.01(.00)***		.01(.00)***	.01(.00)***
Productive		.07(.00)***	.08(.00)***		.09(.00)***	.09(.00)***
Assessment		-.00(.00)**	-.00(.00)*		.01(.00)***	.01(.00)***
Initial Level			.00(.00)			.00(.00)
Random						
Students	.07(.26)	.07(.27)		.05(.22)	.05(.22)	
Week	.00(.01)	.00(.01)		.00(.01)	.00(.01)	
LogLik	-1222.8	-857.1	-836.8	-1183.3	-711.5	-711.7
Obs	5103	5103	4968	5148	5148	4966
Students	189	189	184	198	198	191

*p<0.05; **p<0.01; ***p<0.001

Log-transformation on catchup time. Baseline = Passed students

Standard errors in parentheses for Fixed estimators

Standard deviation in parentheses for Random estimators

After examining the relationship between the timing of engagement and academic performance, I created heatmaps to visualise how students spent time catching up with each study block in the curriculum. This will help educators to pinpoint the exact study materials that students were struggling with. The darker the colour on the heatmap, the more time that students spent on a respective learning activity in that week. A heatmap was created for each group of performance for comparison purposes (Figure 8 - 13). Visual inspections of the heatmaps suggested that students who failed the module spent much less time studying in advance compared to the excellent and passed group. However, all the groups spent time on revising study materials during the last four weeks of the module, as a preparation for the final assessment. What is more interesting is that there were three particular study materials that all the three groups of students spent a lot of time catching up with: Block 2 Part 1, and Block 2 part 2, and Block 2 part 3: case study 1 (Figure 10-13). This implied that students might be struggling with these three topics or the structure of the subsequent activities required students to revisit these three topics frequently.

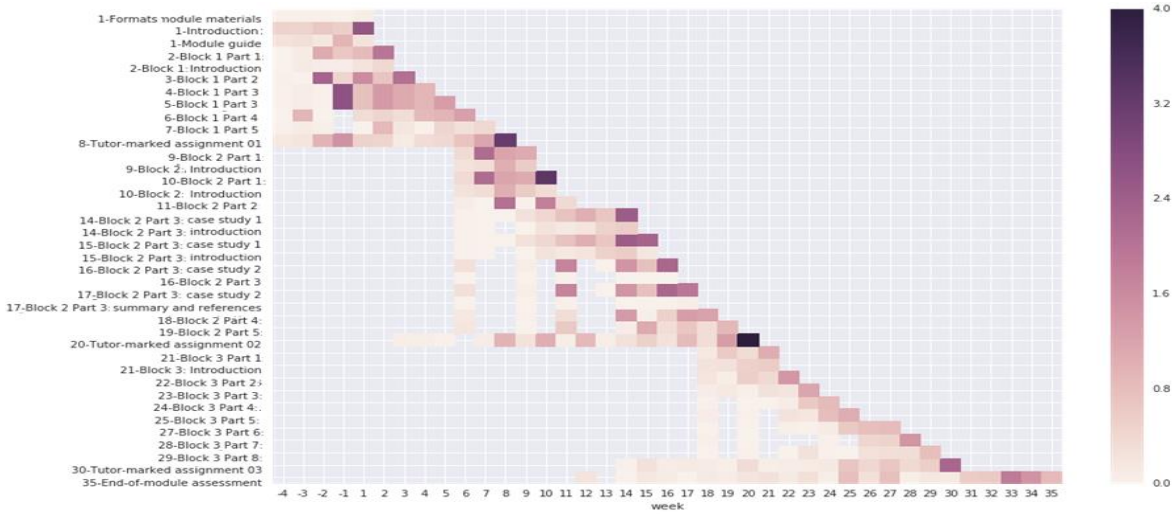

Figure 36. Excellent students spent time studying in advance

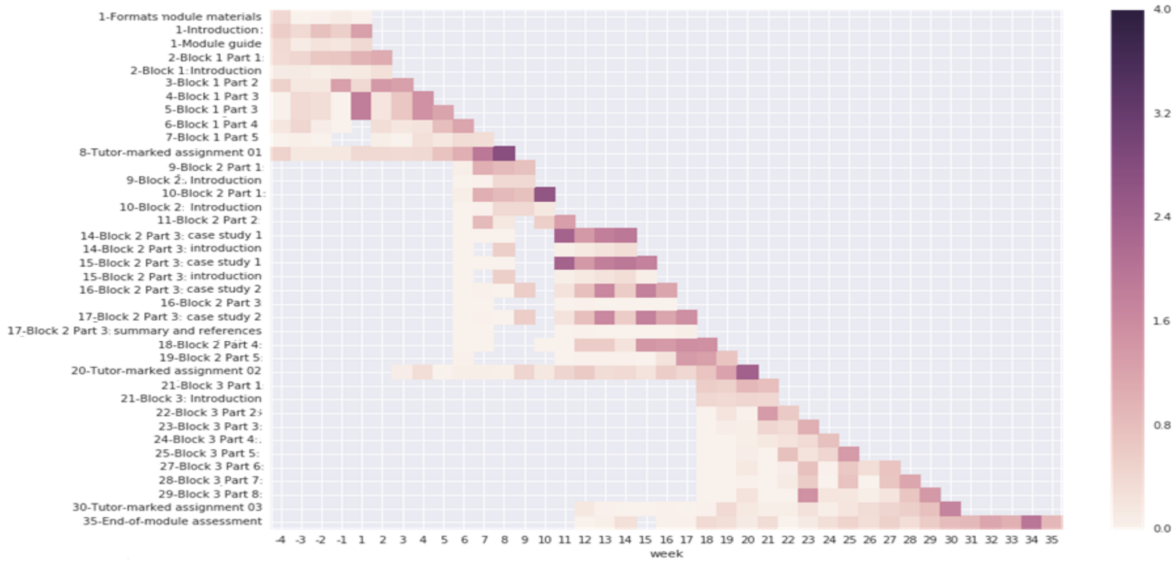

Figure 37. Pass students spent time studying in advance

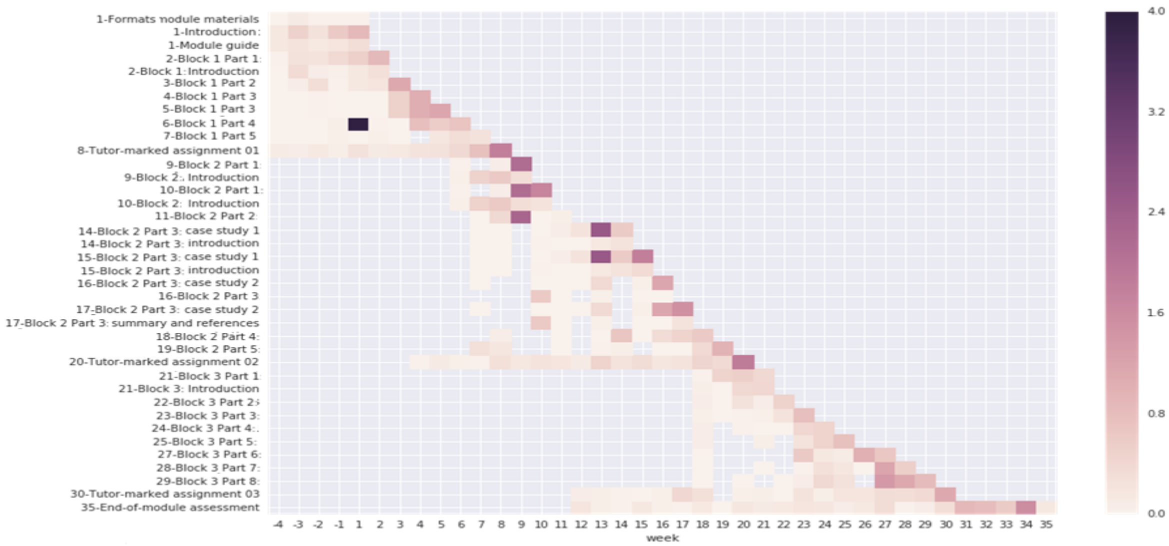

Figure 38. Failed students spent time studying in advance

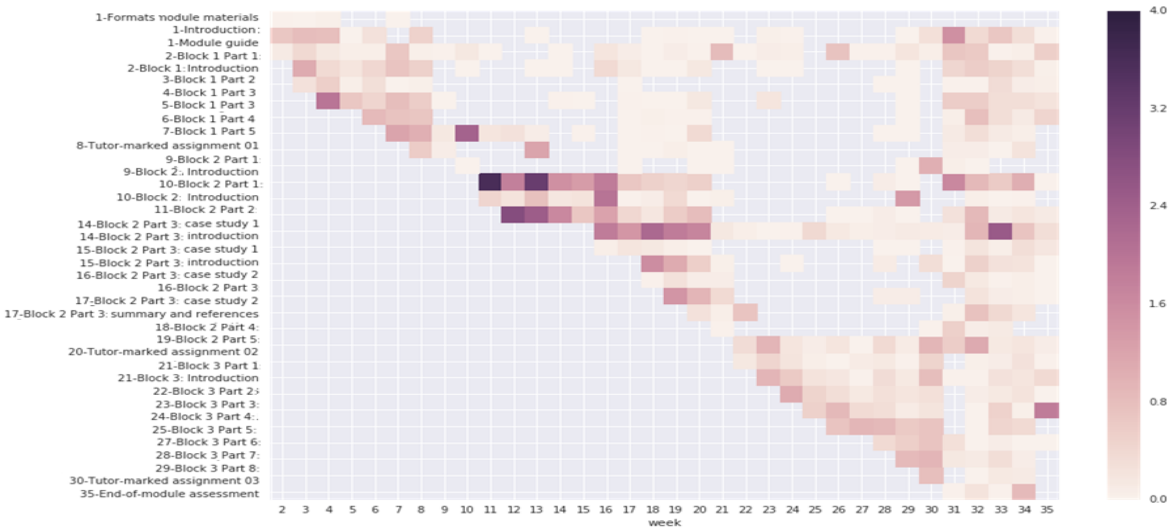

Figure 39. Excellent students spent time on catching up activities

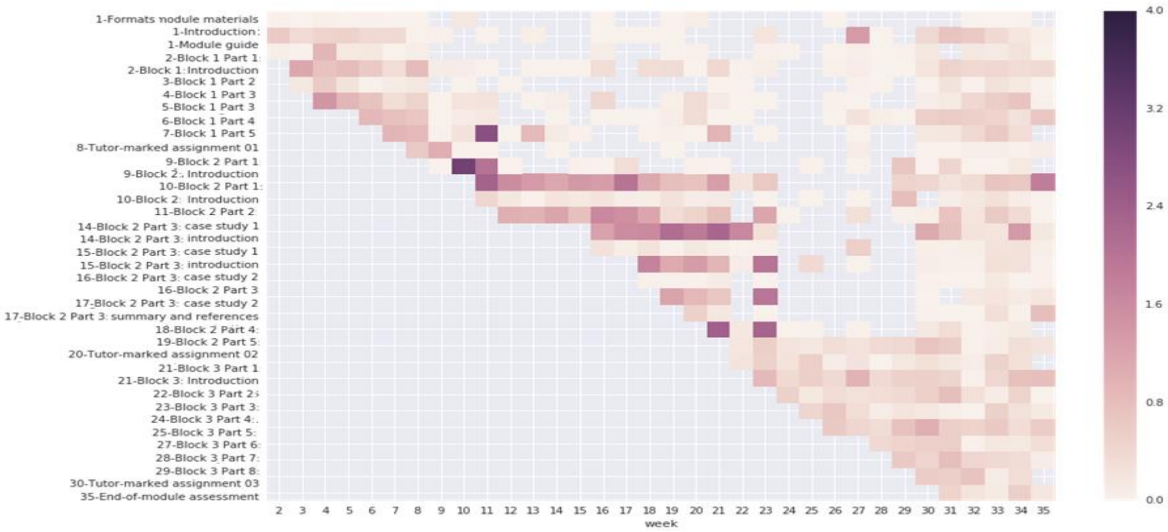

Figure 40. Passed students spent time on catching up activities

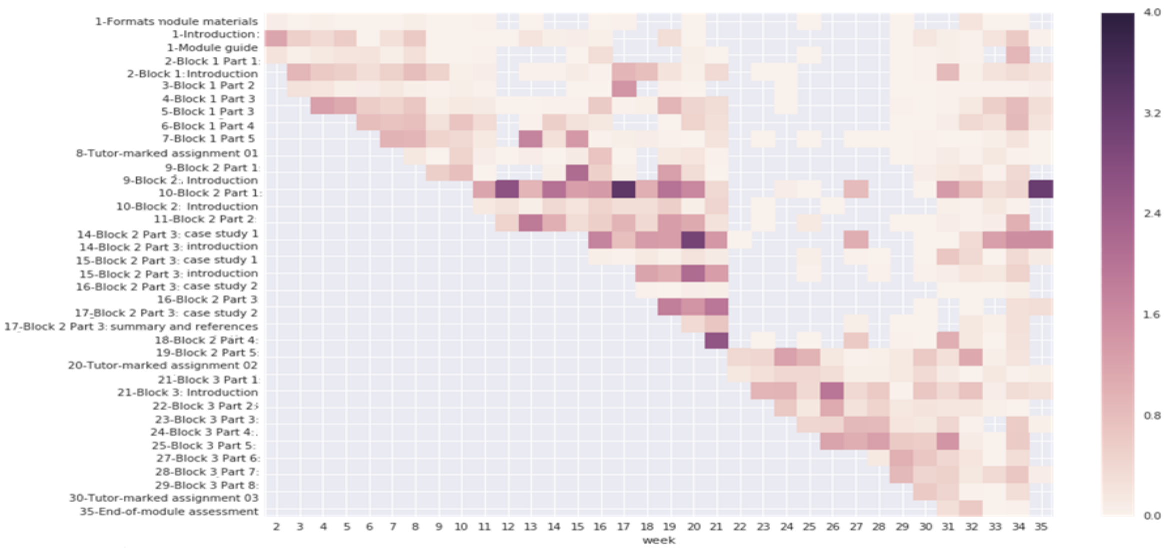

Figure 41. Failed students spent time on catching up activities

7.4 Discussion

RQ4.1 How does students' timing of engagement align with learning design?

Findings from Study 4 indicate the way teachers design for learning significantly influenced how student spent time on VLE, which is in line with previous work (Nguyen, Rienties, et al., 2017b; Nguyen, Rienties, Toetenel, et al., 2017; Rienties & Toetenel, 2016b). While in general the intended LD and actual behaviours followed a similar trend over time, there remained substantial discrepancies between what teachers recommended or expected and the actual time spent on respective learning activities by students. In most weeks, students spent less time (nearly a half) studying the assigned materials on the VLE compared to the number of hours recommended by teachers. One potential explanation could be that the time spent on the VLE only partially represented the actual time spent overall since students could study the same materials outside of the VLE (e.g., downloading PDF files, using other browsers). At the same time, in certain weeks the actual time spent on the assigned materials was equal or above the time recommended by teachers (i.e., week 9, 10, 12, 13). Given that the time spent on the VLE only partially reflected the total time spent on the assigned materials, these discrepancies could signal a major underestimation of the actual workload of the assigned materials. This could potentially discourage and stress out students, given that most of the students in this course also had a part-time or full-time job, as well as potentially other responsibilities (i.e., family, caring responsibilities).

By comparing the assumptions in LD made by teachers with actual student behaviour, LA could act as a reflective resource and provide actionable feedback. For example, teachers could adjust their expected workload of study materials in week 9, 10, 12, 13 and redistribute the workload more equally. At the same time, teachers could examine whether they overestimated the actual workload in week 16, as the LD allocated 13.13 hours while the actual time spent on the same materials on VLE was only 2.89 hours on average. However, adjusting the course schedule might not feasible in certain institutions, which require teachers to provide a detailed schedule in advance for quality-assurance purposes.

Secondly, the analyses have pointed out that the students' actual timing of study engagement could be substantially different from the assigned week. In particular, most students spent more time studying the materials after the week which they were assigned for. Therefore, given most students were also working in parallel to their study, LD should allow for more flexibility in the timing of the study. Moreover, teachers should consider the whole learning process (planning, enacting, and revising) for each learning activity, rather than looking at a learning activity as a single entity occurred only in its assigned week.

One potential implication of Study 4 could be that if students tend to spend more time on catching up on particular learning material, the teachers could check whether the material was clearly explained and provide a quick recap or Q&A for the material in the subsequent weeks. For instance, students across all three groups of performance spent a lot of time catching up on the study materials in week 13, which was a case study. Students continuously spent time catching up on this case study for five weeks after week 13. One explanation could be that many study activities after week 13 were based on this case study, therefore students tended to revisit that salient study material. Alternatively, they could revisit this case study as a part of the preparation for their TMA which was taken place in week 18. Finally, it could be due to the high workload or difficulty level in this case study which required several attempts to complete the task. In either way, the teachers could use this information to support their LD practice.

RQ4.2 How does students' timing of engagement relate to academic performance?

Not only did students exhibit different study patterns compared to the LD, but these study patterns also varied significantly across the three groups of performance. My analysis suggested that excellent students spent the highest amount of time studying both in advance and catching up/revising on the VLE, followed by passed students and failed students. One obvious interpretation could be that the more effort one puts in, the higher the respective learning results will be. However, since the time spent on the VLE only partially captured the total effort, another explanation could be that students who studied on the VLE had better results than the students who studied on other platforms (e.g., off-line, Google).

Even though this order of engagement intensity across the three groups remained the same in both in advance and catching up study patterns, their relative frequency revealed a different story. Given the same study materials, excellent students spent a large amount of time studying in advance, while failed students spent a large proportion of their study time on catching up. These differences became even more prominent towards the end of the course, in which 80-100% of the time spent on the material by failed students was catching up activities, compared to 40-60% for passed and excellent students (Figure 39-41). Interestingly, for the first 10 weeks failed, passed, and excellent students spent roughly the same percentage of study time on catching up. An important implication of this could be that teachers should pay careful attention to students with a high percentage of catching up behaviour from week 10 onwards, as that could be a signal of the students falling behind with their study. Alternatively, providing different pacing or study breaks for students might allow "failing" students to catch a breath, and continue successfully afterwards.

Furthermore, each type of learning activities could significantly influence how much time students' study in advance or catching up. For instance, for assessment activities (such as TMAs), all the three groups of students spent 80-100% of their time studying in advance, with the exception in week 18 in 2016 (Figure 36-38) when failed students spent on average only 60% of the time studying in advance for assessments. However, for productive activities, students were more likely to delay their action (one hour increase in productive activities was associated with a 7.25% increase in the catching up time). Therefore, teachers in this course could re-examine the design of productive activities.

While the analysis has shown significant relations between different types of learning activity, different study patterns, and different groups of performance, readers also need to keep in mind that students are agents. Given the same demographics (age, sex, gender, occupation, education) and the same study pattern, different students might still end up with different results. For example, there was a 5-6% random variance across individuals with a standard deviation ranging from 24-30% (Table 36Table 36. Mixed effect model of time spent on studying catching up and revise). In other words, if student A who spent 30% more or less on studying in advance or catching up than student B, both could still achieve the same outcome (pass the course) in the end.

Finally, Study 4 demonstrated the potential of using LD-informed analytics to generate actionable feedback to help teachers refine their curriculum. Simple analytics based on demographics or behavioural data alone might be limited in what actions can be taken (Tempelaar et al., 2017). For example, Study 4 located three specific blocks of study materials that students might be struggling with. Using this information, teachers can go back and double-check these three learning materials or get some feedback from students on whether they have any problems understanding these three topics.

7.5 Conclusion

In conclusion, Study 4 investigated how students study patterns compare to the initial study regime produced for the LD, together with how different groups of performance and LD were related to these study patterns. The analyses were conducted using trace data from the VLE longitudinally over 28 weeks, with 387 participating students, and replicated over two semesters in 2015 and 2016. The findings indicated that there were discrepancies between how teachers designed for learning and how students studied in reality. In particular, the time spent on the VLE was on average less than the number of hours recommended by teachers in most weeks. The analysis also pointed out that the timing of the study could take place before, during, or after the assigned week. The actual study patterns also varied across different groups of performance. Excellent students on average spent more time studying both in advance and catching up than passed and failed students. At the same time, the percentage of time spent on catching up activities was higher for failed students compared to passed and excellent students. Finally, different types of learning activity could influence how students studied in advance or catching up. The findings also pointed out a large variance between students' engagement in the same performance group. While there were some consistent differences in how different groups of students engaged in learning, there was no 'golden' recipe of how one should study. This suggested that the "design for the average" approach can easily miss out the complexities of how each individual student learn in an online environment.

From a research perspective, Study 4 contributes to the literature by providing empirical evidence of how and when students study compared to the recommended path designed by teachers. The findings reinforced the vital position of LD in the context of LA. Firstly, it is important to incorporate the LD for methodological purpose as it could support LA researchers to refine their measurements (i.e., time-on-task estimation). Although Study 4 only partially addressed this issue of measurement, I encourage future scholars to tailor their duration limit of time-on-task to the content and design of individual activity. Secondly, the inclusion of LD in LA model could help both researchers and practitioners to better interpret the results, which supported the arguments from previous studies (Gašević et al., 2016; Lockyer et al., 2013; Rienties & Toetenel, 2016b). Thirdly, Study 4 showed the importance of temporal characteristics of engagement in LA research, as this could provide a deeper understanding of the learning processes compared to studies with aggregated engagement metrics.

From a teacher perspective, Study 4 makes a step forward to translate LA findings into actionable feedback (Tempelaar et al., 2017). By having a better understanding of how, when students study on which materials, and how these behavioural patterns connected to LD, teachers may be in a much better position to reflect and adjust their teaching practices. By explicitly pointing out which study materials were under or over-used, teachers can act on these materials. This information can be fed back into a LA dashboard, which would support teachers and learning designers to track how the students progressed through each individual study material (on-track or lagging behind). Teachers can use this information to adjust the study workload and re-arrange the structure of learning activities accordingly. Our findings also emphasize the need to keep in mind the whole learning process for each learning activity when designing their course, rather than seeing each activity as a single occasion in its assigned week.

From a student perspective, visualizations of the timing of engagements of peers could act as practical guidelines for students with different learning preferences, and support them to self-regulate their learning (e.g., plan their study time) more efficiently. For example, if the previous cohort spent a lot of time catching up on a particular week or study material, then a new cohort of students can either start studying the materials earlier or reserve more time for catching up in the following weeks. Moreover, students can make use of their own LA visualizations to keep track of their study plan. For instance, students could set up their own study plans (how much time do I spend on this material, what is my deadline, etc.) and use LA visualizations of their actual study behaviour to continuously reflect on their study plans (do I overestimate or underestimate the actual workload, am I following or falling behind with the course schedule, etc.).

Finally, there are some limitations of the current study that should be kept in mind for future research. Firstly, Study 4 was conducted within the context of one online module, which could restrict the generalizability of the study to another context. Our findings can be generalised to most courses at OU and other online courses with a similar design, which is assimilative-oriented and carefully scaffolded. The student population at the OU is unique compared to those at traditional universities. We have an adult population on average, with varying degrees of prior educational backgrounds and often have a full-time or part-time job while studying at the OU. While the first finding might change depending on the context, level of difficulty, and LD of a course, I expect the second finding would remain consistent across different contexts (e.g., high-performing students engage in a timely manner, and low-performing students spend a large portion of their time catching up).

Study 4 only considered students who completed the course for comparison purposes, while students who withdrew might offer additional insights into the findings. While the LD taxonomy has been developed and implemented at the OU for a long period, it could over-simplify the actual LD (i.e., multiple types of assessment such as formative, summative, self-assessment were collapsed into one category). At the same time, keeping a taxonomy concise to be able to generalise to other contexts, yet, detailed to separate different types of learning activity remains a challenging task. Finally, it is important to acknowledge the caveats of using trace data on VLE. While the student behaviour on VLE has contributed to the increasing accuracy of the predictive algorithm of student performance, of course, it does not capture student behaviour outside of VLE or offline.

Study 4 has pointed out some potential issues that teachers could pay attention to. However, further qualitative research is needed (interview with teachers and students), in order to identify the underlying reasons behind these inconsistencies between LD and actual behaviours. Study 4 has implicitly implied that LD ‘causes’ student engagement. However, the causal relationship between LD and student engagement should be further investigated in future research using quasi-experimental interrupted time-series designs or instrumental variables. Furthermore, while a mixed-effect model allows for dependency between an individual’s observations, there might be some dependencies of residuals between individual’s observations, or there may exist a non-linear relationship between week and time-on-task. Therefore, future studies should consider autocorrelation issues in time-series using autoregressive–moving-average (ARMA) models. Nonetheless, this research clearly points towards the need for LA researchers to take time into consideration when modelling LA with LD.

Chapter 8 - General Conclusion and Discussion

The previous chapters have presented findings from four empirical studies that set out to investigate how teachers design for learning, and the impact of learning design on student engagement in a distance learning setting – The Open University UK. This final chapter provides general conclusions and discussions in relation to the research questions and gaps in the current literature. Section 8.1 summarises the overarching objective of the research. Section 8.2 highlights the novel contributions to knowledge to which the studies have contributed. Section 8.3 describes the methodological contributions of this research. Section 8.4 discusses the research limitations, followed by implications for practitioners in Section 8.5. Finally, section 8.6 puts forward suggestions for future research in the domain of LA and LD.

8.1 Introduction

The role of teachers in the 21st century has shifted from delivering information to facilitating and designing learning experience goals (Goodyear, 2015). The increasing development in online and distance education has provided researchers with an unprecedented amount of data generated by both students and educators (Buckingham Shum, 2012). This provides new opportunities to optimise the student learning experience, to improve teaching practices, and to push the boundaries of learning sciences. Learning analytics in the last 10 years has seen tremendous growth in both scholarly research as well as practical applications and policies (Dawson et al., 2019; Viberg et al., 2018). By shedding light into the learning process of students, LA helps teachers to verify their existing assumptions in module design using authentic digital traces of learning activities. At the same time, by capturing and visualising sequences of learning activities designed by teachers, LD provides a contextual overlay to better interpret LA findings (Gašević et al., 2016; Mor et al., 2015; Persico et al., 2015). The connection between LA and LD provides a bridge between data-driven LA research and educational theories (Gašević et al., 2015; Mangaroska et al., 2018; Wise et al., 2015). Without the pedagogical contexts such as LD, it is difficult to interpret analytics findings and offer meaningful insights to teachers and students. By aligning LA with LD, researchers can provide a narrative behind their numbers to translate LA findings into actionable feedback (Rienties & Toetenel, 2016b).

This thesis was built upon the synergy between LA and LD to unpack temporal characteristics of how teachers design for learning and how LD influences student engagement in distance education. In doing so, the thesis has addressed the following research questions:

- RQ1.1 What are the temporal characteristics of learning design?
- RQ1.2 How do different types of learning activity interact with each other?
- RQ2.1 What are the driving factors behind teachers' design decisions?
- RQ2.2 What are the barriers and affordances of learning design adoption at the OU?

- RQ2.3 How do teachers make use of feedback on their module to support learning design?
- RQ3.1 How do learning designs influence student behavioural engagement over time?
- RQ3.2 How do learning designs influence student satisfaction and pass rate?
- RQ4.1 How does students' timing of engagement align with learning design?
- RQ4.2 How does students' timing of engagement relate to academic performance?

The first half of this thesis (Study 1 & 2) captured a dynamic picture of the LD practices at the OU through the lens of LD representations and teachers' perspectives. As discussed in section 2.2.3, there was a lack of research into how LD representations can help us understand how teachers design their courses in an authentic environment (Dagnino et al., 2018). There was also a paucity of empirical studies exploring the time dimension in LD, such as the temporal aspects of LD throughout a module, and how teachers combine different sequences of learning activities over time (Chen et al., 2018; Knight, Friend Wise, et al., 2017a). The OU is one of the few institutions which has implemented LD practices on a large scale and therefore, it provides an ideal opportunity to answer these questions. Study 1 filled in this research gap by uncovering how LD representations of 37 undergraduate modules changed over time and the interplay between different types of learning activities. Another gap in the literature was the shortage of studies exploring LD from teacher perspectives and the affordances as well as barriers in adopting LD practices (Dagnino et al., 2018). Through a series of interviews with 12 module chairs, Study 2 unpacked the complex factors related to students, institution, OULDI, and analytics that influenced the LD practices at the OU. By employing a mixed-method research design, the findings from both studies were triangulated which provided robust and unique contributions to the LD literature.

The second half of this thesis (Study 3 & 4) showcased how LDs influenced student behavioural engagement over time. As pointed out in the literature review section 2.2.3, there remains a shortage of longitudinal studies that connect LD with student behaviour, satisfaction, and performance. Study 3 addressed this gap through a large-scale analysis of 37 modules and weekly engagement of 45,190 undergraduate students at the OU. By comparing weekly design decisions with weekly engagement patterns, Study 3 offered important and unique insights into the dynamic temporal relationships between teacher design and student behaviour. Study 4 took a further step to examine student's timing of engagement and its relation to LD and academic performance. In doing so, Study 4 revealed substantial inconsistencies between student engagement and module design. On average, students spent less time studying on the VLE compared to the suggested workload in their module guide. Moreover, Study 4 shed new light onto the relationships between timing of engagement and academic performance. High-performance spent more time and followed the module timeline, whereas low-performing students spent a large proportion of their studying time on catching up and revisiting previous materials.

The four studies together formed a comprehensive understanding of LD from three different perspectives: LD representation, teacher perspectives, and student behaviour. The studies provided unique insights through unpacking the temporal changes in LD and behavioural engagement over time. A summary of the main findings of this thesis can be found in Table 37.

Table 37. Summary of thesis findings

Study	Sample	Methods	Research Questions	Findings
Study 1	37 modules over 30 weeks	Visualizations Network analysis	**RQ1.1** What are the temporal characteristics of learning design?	• Assimilative, productive, assessment activities were used the most while interactive and communication activities were underused • A negative correlation between assessment activities and other activity types • There was a lot of fluctuations in workload within and between modules
			RQ1.2 How do different types of learning activity interact with each other?	• Strong ties between assimilative and productive activities • Assimilative activities combined words and figures together
Study 2	12 teachers (module chairs)	Semi-structured interview	**RQ2.1** What are the driving factors behind teachers' design decisions?	• Teachers decisions were influenced by management and institutional policies • Teachers tried to maintain a balanced workload • Teachers aimed to build up study skills of students • Teachers involved in co-design and re-design • Teachers valued collaborative activities but found it challenging to implement
			RQ2.2 What are the barriers and affordances of learning design adoption at the OU?	• Teachers found OULDI useful for reflection • Teachers found OULDI becoming a management tool • Teachers found OULDI difficult to interpret • Teachers needed more follow-up activities & practical suggestions from OULDI
			RQ2.3 How do teachers make use of feedback on their module to support learning design?	• Teachers valued feedback from tutors • Teachers were sceptical about course evaluations • Teachers found analytics data useful and wanted a more detailed analysis

Study 3	37 modules and 45,190 students	Fixed - effect modelling	**RQ3.1** How do learning designs influence student behavioural engagement over time?	• LD explained up to 69% of the variance in student engagement • Communication and assessment were positively correlated with engagement
			RQ3.2 How do learning designs influence student satisfaction and pass rate?	• Communication was negatively correlated with satisfaction • The excessive workload was associated with a decrease in the pass rate
Study 4	1 module, 387 students, replicated over two semesters	Multi-level modelling	**RQ4.1** How does students' timing of engagement align with learning design?	• Students' time spent on VLE was half of the expected workload by teachers • Students could engage in advance or catch up and do not always follow the course timeline
			RQ4.2 How does students' timing of engagement relate to academic performance?	• High-performing students spent more time studying than low-performing • High-performing students spent less proportion of their time catching up than low-performing students

8.2 Theoretical Contributions

8.2.1 Learning Design

Contribution 1: Understanding of the temporal changes of LD over time

The field of LD has seen an increasing number of tools and frameworks developed to represent teaching practices and help teachers reflect on their LDs (Cross et al., 2012; Dalziel, 2003; Hernández-Leo et al., 2018; Koper et al., 2004; Laurillard et al., 2018; Law et al., 2017). However, few studies have considered the use of LD representations to explore common trends and variations in LD across modules and disciplines (Toetenel et al., 2016a, 2016b). Previous work has also treated LD as a static entity (AUTCLearningDesign, 2002; Toetenel et al., 2016a), without taking into account the temporal changes in how teachers design for learning over time. By incorporating a longitudinal study design of 37 modules over 30 weeks, this thesis shed new lights on the dynamic temporal characteristics of LD.

Findings from this thesis showed that assimilative activities, such as reading, watching, and listening were predominantly used at the beginning and throughout the module. Assimilative activities were often accompanied by productive activities which required students to reflect on the information they assimilated. Assessment activities were typically introduced every three to four weeks throughout the modules as TMAs, and at the end of the module as an EMA. Assessment activities were negatively correlated with all other activity types, which implied that teachers deliberately reduced the total study workload to ensure students had sufficient time to prepare for their assignments. The assessment strategies varied from module to module. While some modules used a continuous assessment strategy with quizzes every week, others stayed with the standard approach, which included three to five TMAs followed by an EMA or a final exam. Furthermore, the study workload varied from modules to modules and fluctuated considerably from weeks to weeks.

These findings highlighted a mismatch between educational literature, institutional policies, and the actual LDs. Previous research suggested that a balanced and consistent study workload is essential to student success (Bowyer, 2012; Whitelock, Thorpe, et al., 2015). This idea was also reflected in the notional learning time by the Higher education credit framework for England, which suggested 10 hours of learning time per credit[25]. However, in practice the study workload is difficult to estimate due to the quantity and variety of learning activities used by teachers. The effect of inconsistent workload could be even more detrimental to OU students because the majority of

[25] https://www.qaa.ac.uk/docs/qaa/quality-code/explaining-student-workload.pdf?sfvrsn=7f45f981_8

them are engaged in either a full-time or part-time employment in parallel to studying. By visualising LD on a week by week basis, teachers can reflect on the (im)balance of workload in their module and improve their LDs.

Contribution 2: Understanding the interplay between different activity types

The second contribution of this thesis to the LD literature was the consideration of how different learning activity types were combined within an LD. Through network analysis, the findings demonstrated the complexities of how teachers mix and match different types of learning activity across modules. These nuances were perhaps hidden under the current LD representations at the OU because learning activities were mapped into separate categories (Toetenel et al., 2016a, 2016b). The combination of assimilative and productive activities was the main repertoire of practices across 37 modules. Students were given readings, audios, and videos to acquire new knowledge, followed by open questions to facilitate reflections and knowledge transfer of what they have learnt. The use of collaborative and interactive activities was at a minimum in most modules.

This thesis emphasised the importance of going beyond a basic description of learning activities and to recognise each learning activity as an integrated entity within a larger network of resources and pedagogies. Given the same access to resources, each teacher has his/her own interpretation of what constitutes a good LD, and this was reflected through the way each teacher orchestrated learning activities in his/her modules, as indicated in Study 1 and Study 2. Even though all modules put a strong emphasis on assimilative activities type, each module utilised it with other learning activities in different ways. Taking the analogy of cooking, what makes a great dish is a combination of quality ingredients and how the chef combines these ingredients together. Similarly, effective LD is made up of rich resources (i.e., up-to-date learning contents, state-of-art facilities) and good design principles following evidence-based pedagogy.

Contribution 3: Triangulation of teacher perspective with actual LD practices

The third contribution of this thesis is the triangulation of teacher beliefs and experience in LD process with their actual LDs. It was clear from the findings that the LD process at the OU was unique because of its complex protocols as well as the influence from multiple stakeholders, such as department heads, institutional policies, student feedback through course evaluation, tutor feedback, and analytics data. The combination of qualitative and quantitative evidence highlighted the tensions between what teachers valued as good pedagogy and the practical constraints that shaped the products of their LDs.

For example, the visualisation of LDs in Study 1 pointed out a lack of interactive and collaborative activities in LDs. The interviews in Study 2 unpacked some of the underlying reasons behind this issue which was due to resistance from students and tutors as well as the lack of guidelines to design effective online collaboration activities. Furthermore, Study 1 showcased inconsistencies in study workload within modules. At the same time, Study 2 showed that teachers were aware of this problem and deliberately reduced the number of learning activities, moved to a single component assessment strategy, and simplified their instructions. The use of analytical methods such as network analysis and time-on-task estimation based on digital trace data provided a valuable tool to compare and contrast qualitative findings, which supports mixed methods research in education (Creswell & Clark, 2017).

Study 2 also revealed the affordances and barriers that teachers faced when engaging in the LD process at the OU. For example, there were tensions between the teacher's autonomy and the influence of management and institutional policies during the design process, and how the OULDI tool was implemented in practice. This is an important contribution to the field of LD because no other study has explicitly explored the barriers to adoption of LD in an authentic setting (Dagnino et al., 2018). The OU is one of the leading institutions that has implemented LD practices across a large number of modules since 2013 (Rienties et al., 2017). As demonstrated in the findings of Study 2, the LD practices over the years have shifted from a descriptive function to support the LD process to a prescriptive function to manage the LD process. While practitioners perceived some benefits of LD in facilitating conversations among experts and brainstorming on new teaching ideas, the managerial function of LD tools has caused tensions amongst practitioners as they expressed frustrations towards the use of LD as a box-ticking exercise instead of a creative process. The findings provided empirical evidence to support the prediction of Griffiths (2017) which highlighted how LD, as well as LA, could disturb the balance between teacher autonomy and educational management.

8.2.2 Learning Analytics

Contribution 1: Combining LD information with student behaviour to detect whether students were following the course timeline, or falling behind, and correlated different patterns of engagement with academic performance

Previous studies have proposed that LD could inform LA findings by providing a pedagogical context behind numbers (Lockyer et al., 2013). Yet, there is a scarcity of empirical studies that have examined how learning behaviour is shaped by teacher design decisions, especially in longitudinal study design. In light of recent criticism of the gap between LA research and instructional theories (Gašević et al., 2015; Wise et al., 2015), it is important to provide empirical evidence of whether LD could actually improve LA models.

This thesis has substantially contributed to this reported gap by providing large-scale empirical evidence suggesting that LD-informed analytics models explained up to 69% of the variance in student behavioural engagement in a distance learning setting. This contribution is an important bricolage between the field of LA and LD by showcasing that temporal engagement patterns were largely driven by how the courses are designed. By incorporating LD elements into predictive models of student behaviour, LA research can improve model accuracy, and more importantly, it enhanced the interpretability of the findings. Moreover, assessment and communication activities were found to be positively correlated with the duration spent on VLE by students. However, communication activities were negatively correlated with course satisfaction. This confirmed the tensions expressed by teachers that highlighted a potential trade-off between student engagement and student satisfaction when introducing collaborative activities in a distance learning environment. Therefore, it is important to provide teachers with clear guidance based on research in learning sciences and use LA as a test of effectiveness for each LD decision instead of solely depending on course evaluations.

There have been many studies in LA research examining the relationship between time-on-task and academic performance (Kovanovic et al., 2016; Tempelaar et al., 2015). However, previous literature in time management in education also suggested that not only the intensity of engagement (i.e., how much time spent) but also the timing of engagement (i.e., when to engage) will affect academic performance (Claessens et al., 2007; Wolters et al., 2017). This thesis addressed this gap by combining LD information with student behaviour to detect whether students were following the course timeline, or falling behind, and correlated different patterns of engagement with academic performance.

For example, compared to the low-performing group, the high-performing students were found to not only study 'harder' by spending more time but also 'smarter' by engaging more in line with the course timeline. Although flexibility in studying is a prominent feature of distance education, students who were constantly behind the course schedule were more likely to achieve lower performance. Therefore, it is important to design sufficient checkpoints throughout the module to support students who were falling behind before they disengaged with the course and dropped out. This finding has an important implication for LA research by contributing to the development of temporal LA research.

This contribution makes a substantial step forwards to translate learning analytics findings into actionable feedback. By having a better understanding of how and when students study on which materials, and how these behavioural patterns of students connected to learning design, teachers are in a better position to reflect and adjust their teaching practices. By explicitly pointing out which study materials were under- or over used by students, teachers can take evidence-based and data-informed action on these materials. My findings also emphasize the needs to keep in mind the whole learning process for each learning activity when designing their course, rather than seeing each activity as a single occasion in its assigned week.

Contribution 2: Understanding of how LA informed by LD can provide actionable feedback to teachers

This thesis showed that LD plays an important role in LA research by not only improving its model accuracy by taking into account the contextual heterogeneity across modules but also offering concrete and actionable feedback to teachers. As shown in Study 4, the level of engagement on VLE by students was lower than the expected workload by teachers in most weeks throughout the course timeline. What is more important was LA models informed by LD can help teachers to identify problematic learning activities in which students spent an excessive amount of time revisiting or when did students start to fall behind the course timeline.

The field of LA has matured to the point that simple prediction models based on demographics and student behaviour only may not be sufficient to make meaningful changes in curriculum design (Dawson et al., 2019; Gašević et al., 2016; Tempelaar et al., 2017). Many studies in LA have solely focused on optimising model accuracy and applying complex algorithms without thinking about what teachers can do with these predictions. For example, a prediction such as "student X, white male, age 52, who did not submit the 1st assignment, with a low level of engagement, will be likely to fail the course" does not really suggest what actions can be taken by teachers to help this student. We need to go beyond this kind of simple prediction, although it is accurate, to ask the real important questions, such as which concept or learning activity student X was struggling with, and since when student X started falling behind on these activities. Other specific questions about the LD could be asked, such as whether students engaged in material X, how long students spent on learning activity Y, and how often students revisited concept Z. The type of fine-grained analysis illustrated in this thesis allows researchers to ask and answer some of these meaningful questions.

As the LA field is gradually moving towards student-centred analytics by for example providing a dashboard to support student self-regulate their own learning process (Bodily et al., 2017; Matcha et al., 2019), this thesis has some potential implications to the development of future LA dashboards. As shown in Study 3 and Study 4, the behavioural engagement patterns of students were largely driven by the pedagogical context in which the learning activities occurred. Therefore, LA dashboard could embed LD as part of the dashboard's features. For example, the LA dashboard could show which learning activities students have(not) completed and whether they are on-track with the course schedule, or falling behind. Furthermore, recommendations can be given to students based on historical data from previous cohorts. For instance, students can plan their studying time based on information about how much time a previous cohort of students spent each week on learning activities. The dashboard can also highlight key learning materials that high-performing students tend to visit, or the tricky topics that most students revisited many times. As a result, the incorporation of LD into an LA dashboard can reveal a wide range of features that could provide concrete feedback to help students self-regulate their own learning process.

8.3 Methodological Contributions

In addition to contributing to the current knowledge in LD and LA, this research also made several methodological contributions which are outlined as follows.

Contribution 1: Application of network analysis in LD

The application of network analysis in educational research has primarily focused on modelling network structure between students (Cela et al., 2015; Rienties et al., 2018; Wise et al., 2018). However, little attention has been paid to the use of network analysis to model sequences of learning activities (Hora et al., 2013). This thesis showcased a novel application of network analysis to the model “hidden” structure of learning activities and their interactions within an LD. The advantage of using network analysis compared to normal visualisation techniques, such as bar/pie charts (Laurillard et al., 2018; Law et al., 2017), is the consideration of the interplay between different factors in designing a learning task. This entails the type of learning activities (as shown in Study 1) but can also be extended to the learning resources (i.e., library, guidelines, tutors) and the medium to deliver these learning activities (i.e., computer, book, field experiment). The flexibility of network analysis can offset the limitation in learning activity taxonomy, which is restricted by a fixed number of categories that teachers must follow. Network analysis share some similarities with a path diagram which specifies the direction from one activity to the next one, such as the LAMS system developed by Dalziel (2003). However, network analysis provides not only graphical visualisations but also numerical network metrics, such as the degree of centrality or betweenness (Borgatti et al., 2009), that could be useful for the interpretation of the results. These network metrics can also be incorporated into statistical models of LA research as part of the LD features.

This method can be particularly useful for comparison across different LDs, such as identifying similarities between two LDs, or detecting cluster of modules that share the same LDs (Holmes et al., 2019). The method can also be extended to two-mode network modelling to combine a network of students with a network of learning activities to answer, for example, do students in the same group engage in similar learning activities. More sophisticated network models can be used to explore the complex change of network structure of LD in time-series models, such as relational event modelling (Butts, 2008) and exponential random graph models (Snijders et al., 2006).

Contribution 2: Application of LD to create new LA measurements

The second methodological contribution of this thesis is the development of new LA measurements to better understand student behavioural engagement with LD as a reference point. Study 4 elegantly illustrated two very simple but meaningful measurements of engagement, namely ‘catching up' and 'in advance' studying patterns. This simple temporal metric can be extended to more sophisticated ones such as different phases of learning (i.e., planning, operating, revising). The measurement for the timing of engagement is important for future research in temporal LA as well as research in time management and procrastination in education. The incorporation of pedagogical context as a frame of reference into LA models allows new questions to be asked and therefore, creates new measurements that are not available from trace data alone.

Contribution 3: Application of multi-level modelling on the hierarchical data structure to model temporal changes in learning behaviour while incorporating module characteristics

The final methodological contribution is the application of multilevel modelling to explore the effect of LD on student behaviour. Since LA data are often collected at the student level and LD data are collected at the module level, integrating these two types of data together requires the use of multilevel modelling (MLM). As shown in this research, MLM accounted for the differences between modules while allowing for variation between individual students. Compared to the traditional linear regression model, MLM is a more robust approach with higher accuracy by allowing for missing data, controlling for autocorrelation, and accounting for heterogeneity between groups. Future research in the intersection of LA and LD should consider the hierarchical data structure using MLM.

8.4 Practical Implications

My findings have direct implications for the learning designer, teachers, and managers in the future development of LD and LA. These recommendations are based on my personal reflections as well as extensive research activities in the domain of LA and LD during the last three years.

For learning designers

1. **Consider mapping and visualising LD at a weekly level**
   Findings from this thesis have shown the dynamic temporal changes in LD over time and demonstrated how LD visualisation using longitudinal data can help identify potential problems in workload consistency. The use of weekly LD data also supports the comparison with student behaviour using trace data, which are often collected with timestamps.
2. **Have follow-up activities with teachers throughout the module production process**
   From the 12 interviews with OU module chairs, this thesis indicated that only having an LD workshop at the beginning of the module production process might not be effective because teachers need more time to develop a concrete idea about *what* they want to teach, before thinking about *how* they are going to teach. Therefore, having follow-up LD activities throughout the module production process will put teachers in a better position to reflect on their pedagogy and resolve emerging issues as the LD process unfolds.
3. **Combine LD visualisations with analytics of student behaviour**

As illustrated in this thesis, aligning LD with student behaviour is a powerful approach to help both learning designers and teachers test their existing assumptions in LD using real data from students. This will utilise the existing LD representations and show teachers what they can do with this visualisation of LD and how these LD representations can tell teachers something they did not know before.

4. **Carry out an objective evaluation to reflect on existing LD practices**

   Findings from this thesis demonstrated that there are complex underlying factors such as management influence or the timing of LD workshops that influence LD decisions and how teachers engage with LD practices. Having an objective evaluation study (as opposed to small scale "anecdotal" evidence) will help learning designers understand the affordances and barriers that teachers face when engaging in LD practices. By doing so, learning designers can reflect on their own practices and determine how to best support teachers in their LD process.

5. **Have a clear guideline about the use of LD taxonomy**

   This thesis has pointed out that while teachers perceived the LD taxonomy to be useful as a frame of reference, there is ambiguity in interpreting and using the LD taxonomy. Therefore, it is important to provide teachers with a clear guideline of the LD taxonomy, its measurements as well as its limitations. Learning designers can carry out inter-rater reliability test by having multiple learning designers mapping the same content and compare the consistency in figures. Learning designers should also keep in mind that there are on-going developments of other LD taxonomies in the field as shown in section 2.2.2.

6. **Have a better data management process of LD representations.**

   This recommendation is based on my own personal reflection as a researcher who has been working on connecting LA with LD. The current platform (www.learning-designer.open.ac.uk) contains a lot of duplicated and messy LD data created by different people with a wide range of quality. To process these data, I had to manually go through the data, while carried out cross-checking with the online module guide and had multiple conversations with the learning designers to make sure the selected set of data is reliable. This is a time-consuming process and could be improved. There should be a systematic data management practice to ensure the data were entered in a consistent manner. A guideline created to help navigate through the LD data and understand its limitations will be valuable for future research in LD at the OU.

For teachers

1. **Compare pedagogical decisions with actual student behaviour**

   This thesis has shown that while student engagement was largely driven by LD, there are many potential misalignments between what teachers think students do and what they actually do. By having a 'reality check' based on actual student behaviour, teachers can identify potential problems in their LD and make appropriate adjustments. However, teachers should also take the time to understand where these LA metrics come from and be cautious about what they can and cannot inform them.

2. **Create multiple checkpoints with students throughout the course**
   Findings from Study 4 illustrated that low-performing students gradually fell behind with the course schedule and spent a lot of time catching up on previous learning materials. Therefore, it is important to have frequent check-ins with students not only on the designated assignment (TMA) date but throughout their learning process. It might be too late to intervene by the time a student appears as 'at-risk' on the LA system.
3. **Collaborative activities increase student engagement but need careful design**
   The empirical evidence in this thesis suggested that collaborative activities were positively correlated with student engagement but there might be a short-term trade-off in satisfaction scores. Designing collaborative activities in an online learning environment is challenging to say the least. Simply assigning students into groups will not guarantee an effective learning experience. Teachers should consult the extensive literature in online collaborative learning and understand the factors that could influence the student experience in collaborative learning such as trust, group cohesion and demographics as well as cultural background.
4. **Assessment activities have a strong impact on student engagement**
   Another important finding from this thesis was that assessment activities strongly predicted student engagement. Therefore, the design of assessment activities requires careful consideration of different types of assessment (of, for, and as learning) (Earl et al., 2006; Torrance, 2007) and the timing and frequency of assessment that optimise the level of engagement without overloading students.

For managers

1. **Make analytics more fine-grained and more accessible to teachers**
   Findings from this thesis suggested that teachers actively seek out information about how their students are engaging with the module materials. Teachers valued easy access to important KPIs such as TMA submission rate or the number of students accessing certain learning materials. This thesis also demonstrated that LA should go beyond simple click count with more fine-grained metrics such as the duration student spent on each learning activity and whether students are on-track or falling behind. This type of fine-grained analysis tightly linked to LD could provide important new insights to teachers, and may help them to effectively intervene where necessary.
2. **Continuously conduct large-scale testing of pedagogical decisions**

This thesis indicated that communication and assessment activities are the two main drivers of student engagement. However, more testing should be carried out with large sample size and robust research design (e.g., longitudinal design, mixed-method, RCTs, quasi-experimental) to draw any conclusions about the cause and effect of each pedagogical decision. For example, the use of a single assessment component strategy should be evaluated using a combination of student performance, behaviour, and satisfaction. Management must refrain from relying on anecdotal evidence and quick metrics in making pedagogical decisions.

3. **Aware of the unintended consequences when a supportive tool becomes a management tool**
   The famous Goodhart's law states that: "When a measure becomes a target, it ceases to be a good measure". As shown in this thesis, teachers expressed concerns about how LD metrics were used to manage the design process, as opposed to its original objective, which was mainly supportive of the design process. This lesson can be applied to future LA metrics as they become a part of standard practices across institutions. A balance must be retained between the autonomy of teachers when they engage in new LD/LA tools and the desire to use new metrics to evaluate teaching effectiveness.

For the OU and the wider UK HE sector

The results of this thesis shed substantial new and unique lights on learning design patterns at the OU, and the extent to which students' behaviours align with the course design. By incorporating module characteristics and their respective design patterns into learning analytics models, OU teachers can substantially improve their reflections on their courses as well as evaluate the effectiveness of each learning activity or material. This type of design-informed learning analytics model can be used in conjunction with predictive learning analytics models (e.g., OU Analyse) to provide targeted interventions to support at-risk students. For example, when a student was flagged as 'at-risk' by OU Analyse, teachers can take a closer look at this student's engagement patterns (i.e., time-on-task) and identify which learning activities that the student was struggling with. Using this information, teachers can personalize the intervention messages to any at-risk students according to their own learning patterns. For example, if students have not engaged with a key learning concept, an automated reminder could be crafted as "Have you looked at concept A?". If students have engaged with certain activities but seemed to struggle to get through them, a message could be tailored as "You seem to spend a lot of time catching up on activities A, B, and C, what can we do to help?". Continued efforts are needed to make learning analytics findings more actionable using insights from learning design.

By reflecting on the existing engagement patterns with module activities, OU teachers can get a more realistic estimation the actual workload and time spent by students on each learning activity, and possibly identify sub-groups of students who might need more or less time to complete say activity A. Teachers can use this information to update the workload of their learning activities in the next presentation. For instance, instead of having a subjective estimation that activity A is going to take 20 minutes, we could provide a 95% confidence interval of the actual workload exhibited by the previous cohort, such as "Last-year students spent on average 5-10 minutes on this activity". A more accurate workload estimation will be of great importance to the planning and time management of OU students, and help them avoid being overwhelmed because of an unexpected volume of work. Teachers can investigate which learning activity has (not) been used by students, and make appropriate adjustment, such as drawing more attention to key concepts which may have been overlooked, or removing non-essential learning activities that took a lot of time for some groups of students.

Furthermore, study recommendations can be made based on common learning patterns amongst successful students in the previous type of information not only be beneficial to both 'at-risk' students and those who are not at-risk, who might just want to study more efficiently or really want to obtain a deep insight into a particular topic. The current state of learning analytics at the OU, and perhaps across UK higher education, has largely been driven by retention priorities. As a result, there seems to be a greater emphasis on supporting those who are at-risk of failing or dropping out, while limited attention has been paid to helping non-at-risk students to make further improvements. The combination of students' behaviour, design patterns, and academic performance as shown in this thesis can pave a way forward to make improvements across the board of students, and to meet each student's learning need.

As we move forwards to the future, a natural progression of this work is to ensure that these findings are fed back to teachers and students. Current research at the OU have rolled out predictive analytics models (e.g., OU Analyse) across a large number of modules and provided analytics insights to support teachers and practitioners (Herodotou, Hlosta, et al., 2019; Herodotou et al., 2017; Herodotou, Rienties, et al., 2019). However, more work needs to be done to incorporate learning design elements into the development of statistical/machine learning models, and to provide feedback to teachers tailoring to the design of each module. In addition, we should extend the application of LA to OU students and test the extent to which analytics can help students self-regulate their own learning processes in line with recommendation by Ferguson et al. (2017).

Further work should be carried out to establish causal inference through A/B testing or quasi-experimental design in LD. While this thesis has established correlation findings between certain types of learning activities and student engagement on VLE, more work needs to be done to determine causal links between changes in the course design and student engagement as well as performance. The OU has a great potential to be one of the largest experimental laboratories in higher education sector because of the amount data we are collecting. Furthermore, a major strength of the OU is the diverse population of students, which would allow the OU to test diverse LA recommendations to meet the unique learning needs of different groups of learners. Recommendations for learning design should be rigorously tested using a combination of quantitative and qualitative methods before being implemented across the board. There are many great examples of large-scale experiments that the OU could learn from (Kizilcec, 2017, 2019, Chaturapruek, 2018).

8.5 Research Limitations

This research used a mixed-methods approach on longitudinal datasets to unpack the temporal characteristics of the LD process and student engagement on a large scale in one distance learning setting, namely the OU. In doing so, there are some limitations to the research methods and choices adopted that worth noting.

Firstly, the context of all empirical studies in this research was within the OU UK. As noted previously, the OU has a distinctive population of students that might not be generalisable to a traditional population of university students at a face-to-face learning setting, or to any of the diverse distance learning settings. The LD process at the OU was also atypical compared to other universities, in which teachers have some autonomy over the design and production of the LD process and learning materials. Therefore, it would be useful for future research to replicate or validate these findings in a different context.

Secondly, this research explored a large number of LDs with the intentions of describing common patterns and variations across modules. However, this research did not attempt to prescribe which LD or which pedagogy was most effective in this context. To answer this question, the research requires a quasi-experimental design or a randomised control trial, which could take several years to complete, and was beyond the scope of this PhD.

Finally, this research did not ‘close the loop’ by circling the findings back to students and teachers. While the findings from this research have been used in internal reports and informally presented to practitioners through various presentations, there were no formal studies to evaluate the usefulness of these findings and how it could be applied to practices. Similarly, the findings have not been validated by students. Future research is encouraged to embed the methods and findings of this research as part of the interventions and institutional LA initiatives such as OU Analyse.

8.6 Future Research Directions

There are several research directions that could extend the work outlined in this thesis. Firstly, Study 2 from this thesis only considered module chairs as the participants. However, as illustrated in Study 2, the LD process at the OU involves several stages with multiple stakeholders. Therefore, future research should consider the use of an ethnographic approach to explore the dynamics between stakeholders such as learning designers, ALs, curriculum manager, library support, and technicians during the LD process.

Secondly, this research revealed new insights into the temporal processes in LD and student engagement within the duration of 30 weeks (i.e., a semester). However, little is known about the changes in LD practices and student engagement over a longer period of time, such as semesters or years. Therefore, future research should consider extending the longitudinal design, such as examining the changes in LD of the same module over different semesters, the changes in engagement pattern of the same student as they progressed through different LDs, and the changes of LD in the same discipline/qualification from level 1 to 3.

Thirdly, this thesis has demonstrated the advantages of aligning LA with LD. Future research in LA should consider the pedagogical context and the differences between modules when building predictive models using panel datasets (i.e., using multilevel modelling). Future research in LD should embed student demographics, feedback, and behaviour as part of the reflection process to validate their existing assumptions about students.

Finally, there is a lack of studies on how LD-informed LA could be beneficial to students learning progress. For example, recommendation systems could be built based on patterns of engagement of the previous cohort of students to support the subsequent cohorts. Students could use insights from the previous cohort to plan and self-regulate their own learning process such as how much time should they expect to spend on certain learning activities, which concept that students from previous years struggled with, and how high-performing students engaged throughout the course.

Nonetheless, the empirical works carried out in my thesis have demonstrated a strong impact on the development of LA as a field as evidenced by two best paper awards at HCI International 2017 and LAK18. My research in collaborations with OU practitioners has provided important contributions to the teaching and learning practices at the OU, as evidenced by a Research Excellence Award 2018 (runner up) - Impact of Research on OU Teaching & Learning, Curriculum and Students.

8.7 Concluding Remarks

This thesis has investigated the temporal characteristics of LD and student behavioural engagement in a distance learning setting using a mixed-method design on longitudinal datasets of 37 modules and 45,190 undergraduate students over 30 weeks together with interviews of 12 teachers. This work has argued for the benefits of aligning LA with LD which helped uncover new insights and discrepancies between teacher LD and student behaviour. Findings from this research highlighted the need to account for the temporal changes of teaching and learning practices over time and how LD can help translate LA findings into meaningful insights. It is time to go beyond simple predictions based on student data and provide actionable feedback to teachers and students using both LD and LA data and insights.

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Appendix 1: Ethics approval for learning analytics

Human Research Ethics Committee (HREC)

From	Dr Louise Westmarland The Open University Human Research Ethics Committee
Email	louise.westmarland@open.ac.uk
Extension	(6) 52462

To	Quan Nguyen
Project title	Unravelling the dynamics of learning design within and between disciplines in higher education using learning analytics
HREC ref	HREC/2584/NGUYEN
AMS ref	

Memorandum

Date application submitted: 18/05/2017
Date of HREC response: 22/05/2017

This memorandum is to confirm that the research protocol for the above-named research project, as submitted for ethics review, has been given a favourable opinion by HREC Chair's action.

Please note the following:

1. You are responsible for notifying the HREC immediately of any information received by you, or of which you become aware which would cast doubt on, or alter, any information contained in the original application, or a later amendment which would raise questions about the safety and/or continued conduct of the research.

2. It is essential that any proposed amendments to the research are sent to the HREC for review, so they can be recorded and a favourable opinion given prior to any changes being implemented (except only in cases of emergency when the welfare of the participant or researcher is or may be effected).

3. Please include your HREC reference number in any documents or correspondence, also any publicity seeking participants or advertising your research, so it is clear that it has been reviewed by HREC and adheres to OU ethics review processes.

4. You are authorised to present this memorandum to outside bodies such as NHS Research Ethics Committees in support of any application for future research clearance. Also, where there is an external ethics review, a copy of the application and outcome should be sent to the HREC.

5. OU research ethics review procedures are fully compliant with the majority of grant awarding bodies and where they exist, their frameworks for research ethics.

6. At the conclusion of your project, by the date you have stated in your application, you are required to provide the Committee with a final report to reflect how the project has progressed, and importantly whether any ethics issues arose and how they were dealt with. A copy of the final report template can be found on the research ethics website - http://www.open.ac.uk/research/ethics/human-research/human-research-ethics-full-review-process-and-proforma#final_report

Best regards

Dr Louise Westmarland
The Open University Human Research Ethics Committee

Appendix 2: GDPR training certificate

CERTIFICATE of ACHIEVEMENT

This is to certify that

Quan Nguyen

has completed the course

GDPR

July 6, 2018

The Open University

Appendix 3: Ethics approval for interviews

Human Research Ethics Committee (HREC)

From	Dr Louise Westmarland The Open University Human Research Ethics Committee
Email	louise.westmarland@open.ac.uk
Extension	(6) 52462
To	Quan Nguyen
Project title	Unravelling the dynamics of learning design within and between disciplines in higher education using learning analytics
HREC ref	HREC/2693/Nguyen
AMS ref	

Memorandum

Date application submitted: 06/10/2017
Date of HREC response: 20/10/2017

This memorandum is to confirm that the research protocol for the above-named research project, as submitted for ethics review, via a Human Research Ethics Committee Project Registration and Risk Checklist, has been given a favourable opinion by HREC Chair's action.

Please note the following:

1. You are responsible for notifying the HREC immediately of any information received by you, or of which you become aware which would cast doubt on, or alter, any information contained in the original application, or a later amendment which would raise questions about the safety and/or continued conduct of the research.

2. It is essential that any proposed amendments to the research are sent to the HREC for review, so they can be recorded and a favourable opinion given prior to any changes being implemented (except only in cases of emergency when the welfare of the participant or researcher is or may be effected).

3. Please include your HREC reference number in any documents or correspondence, also any publicity seeking participants or advertising your research, so it is clear that it has been reviewed by HREC and adheres to OU ethics review processes.

4. OU research ethics review procedures are fully compliant with the majority of grant awarding bodies and where they exist, their frameworks for research ethics.

Best regards
Dr Louise Westmarland
The Open University Human Research Ethics Committee

Appendix 4: Interview consent form

Interview Consent Form

Research project title: Unravelling the dynamics of learning design within and between disciplines in higher education using learning analytics

Principal Investigator: Quan Nguyen, Institute of Educational Technology, Open University

Thank you for reading the information sheet about the interview sub-study. If you are happy to participate then please complete and sign the form below. Please initial the boxes below to confirm that you agree with each statement:

Please Initial box:

I confirm that I have read and understood the information sheet dated **[DD/MM/YYYY]** and have had the opportunity to ask questions. ☐

I understand that my participation is voluntary and that I am free to withdraw at any time within 30 days after the interview without giving any reason and without there being any negative consequences. In addition, should I not wish to answer any particular question or questions, I am free to decline. ☐

I understand that my responses will be kept strictly confidential. I understand that my name will not be linked with the research materials and will not be identified or identifiable in the report or reports that result from the research. ☐

I agree for this interview to be tape-recorded. I understand that the audio recording made of this interview will be used only for analysis and that extracts from the interview, from which I would not be personally identified, may be used in any conference presentation, report or journal article developed as a result of the research. I understand that no other use will be made of the recording without my written permission, and that no one outside the research team will be allowed access to the original recording. ☐

I agree that my anonymised data will be kept for future research purposes such as publications related to this study after the completion of the study. ☐

I agree to take part in this interview. ☐

Name of participant	Date	Signature
Principal Investigator	Date	Signature

Contact Information

This research has been reviewed and approved by the Open University Research Ethics Board. If you have any further questions or concerns about this study, please contact:

Name of researcher: Quan Nguyen
E-mail: quan.nguyen@open.ac.uk

You can also contact the researcher's supervisor: Prof. Bart Rienties
E-mail: bart.rienties@open.ac.uk

What if I have concerns about this research?

If you are worried about this research, or if you are concerned about how it is being conducted, you can contact Research ethics at The Open University.

Tel: +44 (0)1908 654858
Email research-ethics@open.ac.uk

Appendix 5: Interview Participant Information Sheet

Introduction

Hi, my name is Quan Nguyen, a Ph.D. candidate at the Institute of Educational Technology. I would like to invite you to participate in an interview about your experiences when designing your module and using data in teaching and learning. This study seeks to gain a better understanding of the underlying thought process when teachers design their module in an online learning environment, and how they perceive the use of data in decision making. I believe your experience and expertise as a module chair would provide invaluable insights to this study.

How will this interview be conducted?

The primary researcher (Mr. Quan Nguyen) from the Institute of Educational Technology, Open University will meet with you in person or via Skype voice call. The interview will last approximately 60 minutes. You can expect to be asked questions about your previous experiences in designing your module and your perspective about the use of data in teaching and learning. You will also be given some visualizations of your module's learning design to consider and discuss. The interview will be held in English and will be recorded for analysis.

What other data about me will you receive?

Basic demographics data such as gender, age, years of teaching will also be collected as part of the process.

Are my answers confidential?

Yes. Your name, your module name, module code and any identifying information will be removed from all data. Only the primary researcher (Mr. Quan Nguyen) will have access to the original data. All data will be anonymized before sharing with other research members and will be stored in an encrypted drive.

Who has access to my interview answers?

Only the primary researcher and his supervision team will have access to the anonymized transcript of your interview. We may use excerpts from your interview in the presentation of our findings, both internally at the Open University, and externally, such as in a research journal article. However, you and your associated module will never be referred to by name and all identifying information will be removed.

Am I required to participate?

No. Participating in an interview is entirely optional and you retain the right to withdraw from the study at any time. You may also request to have all, or part of your responses removed from the record up to 90 days after the interview.

Can I change my mind about participating?

Yes. You may cancel your appointment at any time with no consequences. You may also choose to recant part or all of your interview up to 90 days afterwards. To do so, you can contact Quan Nguyen at the contact information listed below.

Are there benefits to participating?

You will receive a copy of the report of the findings from the study, which may serve as a tool for reflection on your teaching practice.

Who can I contact with questions?

You can contact the following members of our research team with questions:

Quan Nguyen

quan.nguyen@open.ac.uk

Prof. Bart Rienties

bart.rienties@open.ac.uk

Prof. Denise Whitelock

denise.whitelock@open.ac.uk

What if I have concerns about this research?

If you are worried about this research, or if you are concerned about how it is being conducted, you can contact Research ethics at The Open University.

Tel: +44 (0)1908 654858
Email research-ethics@open.ac.uk

Appendix 6: Semi-structured interview questions

Research project title: Unravelling the dynamics of learning design in an online learning environment using learning analytics

Principal Investigator: Quan Nguyen, Institute of Educational Technology, Open University

Total Time 60 minutes

The interview will take place at the participant's office, or a meeting room at the Open University UK. A laptop will be used to display data visualizations. No additional equipment is required.

Introduction (2 mins)

- Self-introduction
- Explain the purpose of the interview
- Asking for permission to start recording

Warm up (3 mins)

- Could you please briefly describe your role at the OU?
- Could you please briefly describe the module (who is it for, what is it aiming to achieve)

Theme 1 – Alignment between pedagogy and LD (15 mins)

- What do you want your students to learn from this module?
- How do you structure the module? Why?
- What kinds of learning activities have you designed in this module?
- Why did you choose these activities?
- Who were involved in the module's design process?

Theme 2 – Alignment between OULD mapping and learning design intentions (15 mins)

- What are your first thoughts about this LD representation?
- How does this representation capture your design intentions?
- Is there anything in this representation different from your expectations?

Theme 3 – Perceptions on LA to inform LD (15 mins)

- What kinds of feedback or data that you received on your module?
- What are your thoughts about receiving this information?
- How useful this information is? What did you with it/Any changes with the module?
- Is there any additional information that you would like to receive about the module?

Wrap-up (5 mins)

- Are there any other thoughts or experiences that you would like to share?
- Do you have any further questions?