Inclusiveness in Online Learning Designs: Geo-Cultural and Socioeconomic Perspectives

Thesis

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Inclusiveness in Online Learning Designs: Geo-Cultural and Socioeconomic Perspectives

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Abstract
Initially, there was a strong expectation amongst some in the online learning and teaching community that free, widely advertised, massive, open, online courses (MOOCs) would potentially address the global disparity in educational attainment. However, it turned out that most popular MOOC providers and the majority of active learners still originate from developed countries, mainly in the Global North. Moreover, how successful online learners are in achieving their learning goals found to vary along geo-cultural and socioeconomic dimensions as well as with learning design features. Despite diverse enrolments, most MOOCs adopt a one-size-fits-all design that presents the same set and sequence of learning activities to all learners. This PhD project firstly sets out to study the role of demographic contexts in success in online learning using state of the art predictive modelling methods and data from four large online courses. Then to evaluate the potential link between learners’ geo-cultural and socioeconomic contexts and their successful progression. In total around 60,000 learners from ten courses were included in the analyses. Secondly, the research moves on to study how the learning designs can be adapted at scale in various contexts to improve learners’ persistence. The research leveraged data from the largest MOOC platform in Europe, FutureLearn. In addition, the qualitative data were collected using semi-structured interviews and artefact-mediated questions. The analysis methods included a broad range of algorithms primarily affiliated with Learning Analytics (LA) and Educational Data Mining (EDM), such as decision trees, sequence mining, and cross-validated interactions in survival analysis. Finally, the research investigates the contextual differences in MOOC learners’ perception about various elements of learning design. Therefore, the final mixed-method study used an innovative approach and combined a qualitative method (thematic analysis) with sentiment mining. Overall, the research clearly demonstrated that in comparison to subgroup/interaction analyses, an overall analysis of online learning data can mask geo-cultural and socioeconomic heterogeneity in the correlations between learning design factors and learner persistence. Consequently, overarching data analysis results primarily reflect the behavioural patterns of the largest subgroup, which can stand in contrast to patterns of other, smaller subgroups. Suppose overall data analysis findings are used to guide course design and iterative improvement. In that case, it can lead to improved outcomes for the majority group while leaving behind members of underrepresented groups. This research has therefore made a valuable contribution in solving part of the jigsaw and outlining new directions for the future research as well as highlighting the broader implications that go beyond the domain of learning technologies.
Acknowledgement

In the name of Allah, The Most Gracious and The Most Merciful. In religious terms, I consider myself a Muntazir (one who is waiting), so I had to acknowledge my Muntazar (Awaited, A.S), as they say,

جو تجھ سے عہد وفا استوار رکھتے ہی
علاج گردش لیل و نہار رکھتے ہی

A non-literal, rough translation of this Urdu verse goes as:

*Those that love thee keep, beside them,*

*The cure of the pains of a million heartbreaks*

You must first win tough battles every day, secretly, alone. Then, with a lot of sacrifice and support of your dear ones, you win that final battle based on which the world judges you. Then? You iterate!

I am uniquely fortunate that the circle of my ‘dear ones’ is quite broad (has always been!), so much so that I had to make a list. This is my list.

My father Syed Muhammad Athar Rizvi, and my late mother Bint e Zehra Rizvi.

My supervisor, and mentor, Prof Bart Rienties (to me he means hard work and determination).

My co-supervisor, Dr Jekaterina Rogaten (to me she means strength and boldness).

My co-supervisor, Dr Rene F. Kizilcec (to me he means robustness and thoroughness).

My everything, Syed Danish Raza Rizvi.

My extended everything(s), Jon Ali Rizvi (now four), and Haani Ali Rizvi (now two).

My siblings, particularly my Api, the resolute one; Dr Syeda Kanwal Zehra Rizvi.

My teachers, all, but particularly Dr Sajjad Haider, Dr Shakil A. Khoja, and Dr Hussain Murtuza.

My colleagues at IET OU, all, but particularly Quan, Irina, Hilal, Barbara, Shi Min, Garron, and Maina.

My colleagues / friends from IBA, and my other friends (meri hamjoliyan) from Karachi, Pakistan.

I am submitting my thesis and already feeling extremely proud of this moment. I am unsure what the future holds. However, in the middle of a global pandemic, and between thesis writing, and rewriting, and a heavy imposter syndrome, and unmet childcare needs, and a downright rejection, and a dead-in-water rejection, and a rejection-but-welcome-if-unpaid, and a polite-late rejection, and a third-stage-still-in-file rejection, I received a Confirmation of Offer of Appointment: Research Fellow from UCL Knowledge Lab.
Declaration of Authorship

I declare that the work contained within this thesis is composed by me 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 research outlined in this thesis has been either published or under review in peer-reviewed conference proceedings and reputed journals. Appropriate citations are given to such work throughout. My academic supervisors (Prof Bart Rienties (The Open University, UK), Dr Jekaterina Rogaten (University of the Arts, UK), and Dr Rene F. Kizilcec (Cornell University, US)) are credited co-authorship due to their significant contributions to my research conceptualisation and design. Although co-authors provided detailed comments on each of the full drafts, the publications adapted (outlined below) were created under my own initiation, development, and writing. Dr Shakil A. Khoja is credited co-authorship on the paper related to Study 1 due to his suggestions on the data analysis methods used in this study and his overall encouraging comments on the drafted copies. No publications are given in their entirety or in place of particular chapters. However, significant portions of the publications are adapted within the narrative (particularly Chapter 4 through Chapter 7).

References to Relevant Work:

The empirical work in Chapter 4 has been published as:


The empirical work in Chapter 5 has been published as:


The empirical work in Chapter 6 has been published as:

The work in Chapter 7 has been submitted as:


The brief overview of the work in Chapter 6 and 7 has been published as:

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List of abbreviations

DT – Decision Tree
EDM – Educational Data Mining
EPM – Educational Process Mining
GLOBE – Global Leadership and Organizational Behaviour Effectiveness
IMD – Index of Multiple Deprivation
ITS – Intelligent Tutoring System
KM – Kaplan-Meier
LA – Learning analytics
LD – Learning design
LMS – Learning management system
MOOC – Massive Open Online Course
NCD – National Cultural Dimension
OU – Open University, UK
OULDI – Open University Learning Design Initiative
TA – Thematic analysis
TAM – Technology Acceptance Model
TMA – Tutor marked assessment
UI – User Interface design
UX – User Experience
VLE – Virtual learning environment
Glossary

Culturally adaptive interface designs: Refers to designing software, websites and other web-based resources that adapt their content type (text versus visuals, for example) and look and feel (like colours, interface design, modalities) to suit the visual preferences of users from dissimilar geo-cultural contexts (Reinecke & Bernstein, 2013, 2011).

Culture: ‘Collective complexes of learned behaviours and perceptions of individuals in a society’ (Tylor, 1871)

Decision Trees (DT): A simple yet powerful, multivariate, non-parametric supervised learning method used for nominal classification that assumes an elaborate approach to understand the relationships between independent and dependent variables.

Educational Data Mining (EDM): A sub-field of data mining concerned with “developing methods for exploring the unique types of data that come from educational settings, using those methods to better understand students, and the settings they learn in” (Ferguson, 2012, p. 6).

Educational Process Mining (EPM): Process Mining is a set of emerging techniques aimed at extracting process-related knowledge from the events logs. Educational Process Mining (EPM) is an application of Process Mining techniques in the academic domain.

Learning Analytics (LA): “Learning analytics is the measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimising learning and the environments in which it occurs” (Ferguson, 2012, p. 3)

Learning Design (LD): The outcome of a process of course development where the designers create various pedagogical constructs such as a series of learner-facing activities containing different types of learning materials (e.g., reading activities, learning material consisting of audio or video content).

Persistence: The proportion of learning activities accessed before dropout (an approach mentioned by Singer, 2019; and used by Kizilcec et al., 2017; Reich, J., 2014 etc.).

Sentiment analysis: Machine learning methods used to scrutinise the words for positive and negative emotions in the relevant context, often referred to as analysis of affect in text data.

Survival analysis: A branch of statistics for analysing the expected duration of time until one event occurs, often referred to as Time-to-event (TTE) analysis.

Variant: In EPM this term refers to a simplistic view of the end-to-end sequence of activities, analogous to a learning path followed by a significant number of learners.
Chapter 1 Introduction

1.1 BACKGROUND

Over the past decade, open online learning environments have changed the educational landscape all around the world. Increasingly, formal degrees are taking a hybrid form or being replaced by digital literacy products, such as Massive Open Online Courses (MOOCs) (Shah, 2019). As large-scale, freely accessible learning environments, MOOCs are primarily recognized for their potential to facilitate universal learning access. These courses allow learning without any restrictions as long as learners can access appropriate resources such as computers, laptops, mobile devices, and an adequate internet connection (Jansen & Schuwer, 2015). In contrast to the expectations of MOOC enthusiasts (see, for example, Agarwal, 2013; Pappano, 2012), there is substantial inequality and disparity in the global digital learning landscape (Bozkurt & Aydin, 2018; Jansen & Schuwer, 2015). As discussed in Chapter 2 in detail, emerging data increasingly suggest varied persistence and achievement gaps for MOOC learners from various contexts (Reich & Ruipérez-Valiente, 2019). Despite the continuous media coverage (Pappano, 2012; Shah, 2019) and regardless of the benefits associated with the massive open online learning environment, the enrolment and completion rates are still not distributed equally across the globe.

Current research on open online learning environments has provided evidence for a strong link between learners’ demographics and their academic outcomes. A large and growing body of empirical research (as reviewed in section 2.2 in Chapter 2) has identified characteristics such as geographical location or country of residence (Bozkurt & Aydin, 2018; Z. Liu et al., 2016), socioeconomic status (Stich & Reeves, 2017; Hansen & Reich, 2015), age range (Boyte-Eckis et al., 2018; Ke & Kwak, 2013), gender (Nistor, 2013; McSporran & Young, 2001), disability status (Muilenburg & Berge, 2005; Richardson, 2009, 2015), and previous education (Castaño-Muñoz et al., 2017; Wladis et al., 2014) may influence performance in online learning. At the same time, several barriers can impair the achievement of learners originating from certain regions (in the case of MOOCs, primarily from the less affluent regions, located in the Global South). The global disparity can be caused by numerous preventing factors, such as insufficient provision of technical resources and internet, (English) language proficiency, formal and digital literacy levels, and incentives associated with successful participation. Chapter 2 discusses how the relevant literature repeatedly points to various regional and geo-cultural factors that may influence the way learners engage with MOOCs (Reich & Ruipérez-Valiente, 2019; Kizilcec et al., 2017; Kizilcec & Halawa, 2015; Ogan et al., 2015; Guo & Reinecke, 2014).
In addition to the contexts, the way online courses are designed may impact learners’ engagement. In fact, the critical role of pedagogical and course learning design related factors in learners persistence and performance has been widely acknowledged in formal learning environments (Nguyen et al., 2017; Rienties et al., 2017; Rienties & Toetenel, 2016) as well as in MOOC learning environments (Rizvi et al., 2020; Xing, 2019). Current research conceptualises course learning design (LD) as the outcome of a process of course development where the designers create various pedagogical constructs such as a series of learner-facing activities containing different types of learning materials (e.g., reading activities, learning material consisting of audio or video content) (Rizvi et al., 2020; Sharples, 2015). Overall, learning design refers to the development of a course as a sequence of learning activities of different types (instructional videos, articles, quizzes etc.) developed following the learning objectives. The sequenced activities are designed for learning, and therefore can be reused repeatedly, when needed.

MOOCs have received substantial criticism for large enrolments yet low persistence rates (Reich & Ruipérez-Valiente, 2019). Yet the literature on challenges associated with MOOC learners’ persistence has often examined learners’ interaction, specifically with various elements of learning design, for example, text-based resources (Rizvi et al., 2020; Uchiduno et al., 2018), instructional videos (Davis, 2019; Guo et al., 2014), course assessments (Li & Baker, 2018; Juhaňák et al., 2017), and participation in discussion forums (Allon et al., 2016; Sunar et al., 2016; Yang et al., 2013). Since learning activities and the sequence of those activities are a few of the key elements that influence the effectiveness of a course design, it is pivotal to understand the differentiation in learners’ progression and their engagement with various types of activities.

As discussed in detail in Chapter 2, the way MOOCs are designed – in short, LD – can substantially influence learners’ persistence in MOOCs. Typically, this entails various types of learning activities offered in a predetermined order. Recent literature suggests that a centralised learning design (LD) containing a fixed number of sequenced learning resources may be convenient and beneficial for most learners (Bearman et al., 2020). But the same literature cautions that a centralised learning design may not guarantee an increased resource utilisation. Furthermore, a centralised learning design containing prearranged, fixed number of activity types may not work for all learners (see for example Bearman et al., 2020; Margaryan et al., 2015). LD and other pedagogical factors (e.g., teaching methods and content) may have a predictive and causal link with learners’ progression and whether they drop out or stay in the course (as indicated by Xing, 2019; and Guo et al., 2014).

In various regions, the originating culture strongly influences the respective course design and content of the curriculum as well as formal classroom practices (Bozkurt & Aydin, 2018; Arnove et al., 2012). Previous research has suggested that learners’ experiences and reactions to their educational practices may be grounded in and shaped by their culture and geographic region. In
the context of online learning, regional and cultural differences in learner persistence have been frequently reported (Reich & Ruipérez-Valiente, 2019; Rizvi et al., 2019; Kizilcec & Halawa, 2015). Several large-scale studies presented in Chapter 2 have cited continuous disproportional participation and subsequent preference for a particular type of learning activities among MOOC learners from all around the world (Kizilcec, et al., 2017; Z. Liu et al., 2016; Ruipérez-Valiente, Halawa, et al., 2020; Ruipérez-Valiente, Jenner, et al., 2020; Reich & Ruipérez-Valiente, 2019). Moreover, the potential influence of regional, cultural and socioeconomic factors on engagement and persistence in online learning is evident from the literature (Rizvi et al., 2019; Reich & Ruipérez-Valiente, 2019; Allione & Stein, 2016; Guo & Reinecke, 2014). Other financial, technology-related, psychological or social barriers were also repeatedly reported in region-specific research (Castaño-Muñoz et al., 2017; Kizilcec et al., 2017; Hansen & Reich, 2015). In fact, Ruipérez et al. (2020) recently pointed out that demographic differences between course enrolment and completion may have partly stemmed from the distinct design differences between regional and global MOOC providers. Overall, in MOOC learning environments, regional, financial or socioeconomic indicators have long helped researchers understand learners' decisions to enrol, persist or withdraw from a course (Reich & Ruipérez-Valiente, 2019; Hansen & Reich, 2015; Wladis et al., 2015).

In terms of learning designs, the open online courses are designed to appeal to and then retain more learners. To achieve this goal, the designers aim to make the acquisition of course content (that is, textual, visual or auditory information) natural and easy for learners (Sergis et al., 2017; Rai & Chunrao, 2016; Margaryan et al., 2015). What remains unclear from the literature is if the potential influence of course learning design varies between the various contexts, and with time, as the course progresses. The widely reported global divide in the way learners engage with various types of learning and assessment resources points that there may be, indeed, a predictive link between learning design and learners' persistence. To date, limited MOOC research has evaluated how to adapt and tailor LD accordingly (Joksimović et al., 2017). One way to approach this issue could be designing a MOOC that adapts itself to the dynamic needs of learners from dissimilar contexts; however, this could be pedagogically challenging. Still, given the recent advancements in the field of learning technologies, this goal is not unachievable.

Finally, certain learning design factors can easily be made flexible and modifiable either midway or between the course runs. These factors include learning activity types, sequence of those activities and content language difficulty level. Indeed, it is imperative to understand how learners’ persistence is potentially linked with different learning activities in a course design. But much of the work done in this regard has relied on learners’ in-situ data from the MOOC logs to evaluate quantifiable and measurable behavioural engagement patterns without analysing the potential differences in learners’ perceptions. In addition to the above, taking a qualitative approach to
examine learners’ varied perspectives about various elements of learning design may yield even more interesting results. The work presented in this thesis went beyond a general understanding of design and contexts and aims to explore the interlinked nature of both using the in-situ learners’ interaction data, as well as their self-reported perceptions. Altogether the research findings will contribute new useful insights into contextual differences in online learning and their link with the learning designs.

All in all, to the best of my knowledge, few researchers to date have systematically examined the measurable differences in learning behaviours in a large number of courses, even fewer with a focus on geo-cultural and socioeconomic contexts from across the globe. Previous work has evaluated whether there are indeed differences in online learning activity preferences (Bearman et al., 2020; Margaryan et al., 2015). What is less clear is the nature of the predictive link between learning design elements and learners’ persistence, or how and in what ways the predictive link varies between the contexts. Next, given the lack of qualitative evidence in learning behavioural differences, it is still unclear whether there are differences across dissimilar contexts, in how learners perceive various learning design elements towards successful learning in MOOCs. This indicates a need to understand the various associations between learning designs and MOOC learners’ engagement and how the association varies across contexts. This PhD research seeks to address these gaps in our scientific understanding.

1.2 RESEARCH AIMS

The overarching aim of this thesis is first to examine the role of demographic contexts in successful online learning. Second, to evaluate the link between learning designs and learners’ engagement in MOOC learning environments. Third, the research aims to empirically examine the extent to which the association varies between various contexts. Finally, the thesis assesses the contextual differences in learners’ perspectives about the role of learning design towards their engagement in a MOOC. The research project was conducted through four interlinked studies, one leading to the other. The remainder of this thesis outlines the four studies undertaken in order to accomplish these goals. Each study in this project addresses a set of research questions, as summarised below in this section.

As discussed in detail in the next chapter, the relevant work has reported a predictive association between online learners’ contextual characteristics and learning outcomes. The relevance of these characteristics was supported by the studies that have also indicated that each characteristic may affect success differently in the online learning environment. At the same time, previous literature found that learning design might influence the way learners engage with a course. However, it is unclear whether a large number of demographic characteristics can be used collectively to predict online learners’ performance. Also, the extent to which the predictive contribution of various
demographic characteristics varies between the courses. This gap in existing knowledge has led to Study 1 presented in this thesis (discussed in detail in Chapter 4).

Study 1: The role of learners’ contexts in online learning (Chapter 4).

RQ 1.1^1 To what extent is there an association between learners’ demographic characteristics (i.e., regional context, socioeconomic context, education, age, gender, and disability) and online learning outcomes throughout the online course?

RQ 1.2 To what extent does the association (from RQ 1.1) vary across different online courses with distinct learning designs?

Since various types of learning activities and the sequence of those activities may have a key role in an effective learning design, it is critical to examine the ways learners engage with various types of activities and how do they progress in a course? Against this background, this research aims to understand learners’ experiences by examining their progression and engagement with various learning design elements in the open online learning environment. (Study 2; results from Study 2 have been presented in Chapter 5). Moreover, as discussed briefly in the last section and in detail in Chapter 2, several contextual characteristics and regional, cultural, or socioeconomic indicators have long supported researchers to understand MOOC learners’ engagement and persistence. Thereof, a continuation of the research goal for Study 2, the study further explores the differences in activity engagement patterns across various geo-cultural and socioeconomic contexts (see Chapter 5).

Study 2: Learners’ engagement with different learning design elements and their progression through the course; how the engagement varies with learners geo-cultural and socioeconomic contexts? (Chapter 5)

RQ 2.1 How and to what extent does engagement with different learning design elements (i.e., (a) assimilative learning activities (e.g., articles, videos), (b) communication activities (e.g., discussions), and (c) assessment activities (e.g., quizzes)) differ between learners?

RQ 2.2 How and to what extent do temporal learning paths (i.e., sequences of learning activities) differ between learners?

RQ 2.3 How and to what extent does engagement with different learning design elements differ between the geo-cultural contexts?

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^1 The whole number part in research questions refers to the study number and the fractional part represents the actual question. That is, RQ 1.2 implies second research question in Study 1 and so on.
RQ 2.4 How and to what extent does engagement with different learning design elements differ between the socioeconomic contexts?

There is still a clear paucity of research on any potential predictive link between different elements of learning design and learners’ persistence in a course. Therefore, one motivation behind this research was that limited research has explored how different proportions of the various learning activity type (reading material, instructional videos, quizzes, and discussion-based activities) in a course can be potentially linked with MOOC learners’ persistence. Study 3 in this thesis aims to assess the extent to which there may be a predictive link (see Chapter 6). This limited focus in existing literature has also provided a rationale for the two subsequent research questions in this thesis, exploring how and to what extent the predictive influence of learning design varies with geo-cultural and socioeconomic contexts (see Study 3, Chapter 6).

Study 3: Predictive link between learning design elements and persistence; Contextual differences (Chapter 6).

RQ 3.1 How and to what extent does the number of learning design elements (i.e., (a) assimilative learning activities (e.g., articles, videos), (b) communication activities (e.g., discussions), and (c) assessment activities (e.g., quizzes) in a course predict learners’ persistence?

RQ 3.2 How and to what extent does the association between learning design elements and learner persistence (from RQ 3.1) differ between geo-cultural contexts?

RQ 3.3 How and to what extent does the association between learning design elements and learner persistence (from RQ 3.1) differ between socioeconomic contexts?

Previous work suggests that various geo-cultural groups may have distinct preferences for particular learning activities. Section 2.6 in Chapter 2 discusses the likely differences in learning design preferences across various geo-cultural contexts. What we know about the potential link between learning design and persistence is largely based upon quantitative studies that examine MOOC learners’ log data. Nonetheless, most of the existing work about MOOC learning engagement fails to incorporate the variety in learners’ different contexts and how it may have influenced learners’ perceptions about the role of learning design. Therefore, the final study, Study 4 in this project utilised a qualitative method (that is, semi-structured interviews) to collect information on MOOC learners’ perceptions of various learning activities in a course design. The final study in this project used a qualitative and mixed-method approach to unpack learners’ various perspectives about learning activities in a MOOC learning design. Study 4 in this thesis focuses explicitly on learners’ perceptions (Chapter 7 provides more detail about Study 4). This final piece of research presented in this thesis examines the contextual differences in learners’
perceptions and their self-reported experiences with various types of learning activities (see Chapter 7).

**Study 4: Learners' perception of various learning design elements; Contextual differences (Chapter 7).**

**RQ 4.1** What are learners' perceptions of various learning design elements (i.e., activity types, predetermined path) in relation to their engagement in the course?

**RQ 4.2** In what ways do learners' perceptions (from RQ 4.1) differ between geo-cultural contexts?

Recently, extensive work has informed of a global disparity in open online learning, both in terms of enrolment and in the ways, learners engage with various elements of learning designs. However, there is a need for more empirical and/or mixed-method research to investigate in what ways learning design may be linked with the progress of different learners from dissimilar backgrounds. The research project discussed in this thesis was set out against this background. The following section provides a more detailed explanation of the structure of the thesis.

### 1.3 THESIS STRUCTURE

A large part of the research presented in this thesis is quantitative in nature. However, towards the end of this research project, a mixed-method approach is adopted. This methodological transition supported a more nuanced understanding of learners’ experiences with different aspects of learning design as well as provided a way to understand the role of language of instruction (see Chapters 2 and 7 for more detail). This introductory Chapter 1 briefly discusses the context of this research. The remaining chapters in this thesis start with an overview of the literature on the dynamic role of demographics in online learning, the importance of learning designs and engagement differences across different contexts. The subsequent chapters discuss the overarching methodology employed in this research, followed by the methods and results for four interconnected studies. The thesis concludes with a final chapter on general discussion and conclusion. Overall, the structure of the remaining chapters in this thesis is as follows:

**Chapter 2: Literature Review**

Chapter 2 presents an in-depth review of the recent literature on the potential predictive role of learners’ demographic characteristics, differentiation in learning behaviour and perceptions, in general, and across geo-cultural and socioeconomic contexts. This chapter also discusses the learning design theoretical framework this research uses to abstract various learning activities. After reviewing the existing gap in relevant research, the chapter provides rationales for each of the individual research questions addressed in this PhD project.
Chapter 3: Methodology

Chapter 3 presents an overarching view of the methodology used in this research. The chapter starts with a justification for the pragmatic approach. It then moves on to the various methodological approaches used to address the research questions. A more specific evaluation of methods used in the four interlinked studies are further shared in the corresponding chapters (Chapter 5 through 7).

Chapter 4: Study 1. The role of learners’ contexts in online learning; Methods and Results

Chapter 4 examines the first two research questions (RQ 1.1 and RQ 1.2) and unpack the predictive role of six demographic characteristics in successful online learning. The chapter discusses the study settings, instruments, and data analysis methods. One part of this chapter outlines the specific explanatory method used in Study 1. The study found, for example, that the predictive contribution (importance) of each characteristic varied slightly between distinct learning designs. Empirical evidence is offered for the critical predictive role of location and socioeconomic context in learning outcomes. The various limitations of Study 1 and implications for future work conducted in the thesis are also discussed.

Chapter 5: Study 2. Learners’ progression and engagement differences across various geo-cultural and socioeconomic contexts; Methods and Results

Chapter 5 deals with the learning processes and engagement with various learning design elements, in general, and then in dissimilar contexts (that is, research problem addressed through RQ 2.1 to RQ 2.4). The first section in this chapter draws together the methodology and data analysis approaches. The findings from Study 2 presented in the latter part of the chapter indicated measurable differences in learning processes and engagement with various elements of learning designs. The same study also emphasised how the said differentiation varied across various geo-cultural and socioeconomic contexts.

Chapter 6: Study 3. Contextual differences in the predictive link between learning design elements and persistence; Methods and Results

Study 3 explores the extent to which there is a quantifiable link between learning design and learner persistence. Also, if the link varies between different geo-cultural and socioeconomic contexts? After sharing the methods used to answer the respective research questions (RQ 3.1 through RQ 3.3), the chapter examines first the predictive association between the number of learning activities and learners’ persistence in the MOOC. It then explores certain activity types that were an enabler for one context while limiting for another. Various sections then further evaluate the empirical
evidence of how the variation in learning design elements interacted with learners geo-cultural and socioeconomic contexts.

Chapter 7: Study 4. Contextual differences in learners’ perception of various learning design elements; Methods and Results

Finally, Study 4, as reported in Chapter 7, examines learners’ perception of learning design and their experience with various learning design elements. The chapter starts with a brief discussion of innovative mixed methods used in Study 4. Perceptions may be linked with persistence and long-term engagement (see Chapter 2 for more detail). Therefore, the chapter highlights the commonalities or differences between the perspectives of study participants from different geo-cultural contexts and how their self-reported experiences may be linked with their engagement with MOOC learning resources.

Chapter 8: General Conclusions and Discussion

This final chapter provides conclusions, then presents the novel theoretical and methodological contributions this research has offered. In the process, the chapter synthesises the findings from four interlinked studies. In total data from more than 60,000 online learners were examined in three empirical studies (Study 1 through Study 3), followed by a mixed-method study (Study 4) where qualitative data were collected from 22 learners. Building upon the results from Chapters 4 through 7, a section in this chapter discusses the implications for practice. Finally, Chapter 8 concludes the thesis by presenting the overarching limitations of this research and directions for future research.

1.4 CONCLUSION

How learners from dissimilar contexts may have distinct preferences and therefore may benefit differentially from different types of learning activities is of critical scientific and practical importance. In this thesis I argue that learners’ activity preferences should be considered when designing online courses, particularly those aiming for the international education landscape. However, tailoring to the diverse learners may require incorporating an (over)abundance of various types of learning activities (e.g., reading material, instructional videos, assessment activities) in a course. This research provides a scientific basis for multiple course learning designs, each with a distinct structure (e.g., video-heavy, discussion intensive, reading-based). Further research is needed to understand the causes behind contextual differences in learner preferences, specifically those beyond geo-cultural or regional dimensions. Other potential causes worth exploring include learners’ digital literacy level, enrolment motivation, (English-)language proficiency, and course subject area or discipline. A few potential directions of research beyond the reported findings in this thesis will be explored in Chapter 8.
This part has provided an introduction of the research context and summarised the work described in the remaining chapters of this thesis. Overall, the sections above briefly evaluated the role of learners’ contexts in their progress. It then argued the role of learning design and the cross-cultural differences in learning design preferences as distinguished in the previous literature and laid the foundation for the next chapter, Chapter 2. This second chapter in this thesis discusses the existing body of knowledge on these topics and highlights the literature gap, which then led to the research questions. The review combines a multitude of concepts used in this research project. The next part moves on to define Massive Open Online Courses (MOOCs), followed by a discussion on MOOC learning designs, and learning processes. Sharing a few of the most used conceptual frameworks, it presents a debate on the culture-specific learning design preferences revealed in previous literature.
Chapter 2 Literature Review

2.1 INTRODUCTION

A large and growing body of research in learning technology has revealed the significance of online learning designs and the central role of learners’ contexts in successful online learning. This chapter reviews prominent work from the recent literature. Iterative selection and filtering were used to explore the recent literature concerning learning in online learning environments. The chapter is divided into different sections as follows. It starts with section 2.2, which discusses selected studies that have used one or more demographic characteristics to predict learners’ performance in online or blended learning. Overall, the section provides an overview of learners’ demographic characteristics influencing success in online learning. It also highlights the gaps in the existing literature and provides bases for the first two questions (RQ 1.1 and RQ 1.2) addressed in this thesis.

Section 2.3 presents a definition of a Massive Open Online Course (MOOC) learning environment. The narrative throughout this thesis will get back to this definition time and again. The following section 2.4 provides an overview of the theoretical groundings for the learning designs used at the Open University and the FutureLearn MOOC platform. The same section discusses the importance of learning processes, highlights the limitations in the existing literature, and lays a foundation for the next three questions. Next, section 2.5 provides a detailed view of the role of geo-cultural and socioeconomic contexts in the online and blended learning environment. After discussing the various conceptual frameworks for geo-cultural and socioeconomic categorization, the rest of the six research questions are presented along with their links with the first two research questions. Section 2.6 debates four key cultural differences in learners’ perspectives about various elements of learning design, as reported in previous literature. Finally, section 2.7 then concludes the chapter by summarising the key questions this research sought to answer.

2.2 DEMOGRAPHICS AND ONLINE LEARNING PERFORMANCE

This section reviews the literature on learners’ performance prediction. Given the context of the research topic, the review mainly focuses on the work where researchers used one or multiple demographic characteristics, primarily in combination with other variables, to predict learners’ persistence, engagement, or performance in blended or online learning.

Advancements in Educational technology\(^2\) have permitted stakeholders to collect voluminous data from online learners. The data contain information about learners’ demographics and their

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\(^2\) A common definition of Educational technology is “the study and ethical practice of facilitating learning and improving performance by creating, using, and managing appropriate technological processes and resources.” (Januszewski & Molenda, 2013, p. 1)
interactions with other learners and/or learning resources. Numerous studies have leveraged these data to understand learners’ engagement behaviour. An emerging trend in the fields of Learning Analytics\(^3\) (LA) and Educational Data Mining\(^4\) (EDM) is to employ various algorithmic systems to identify and support learners at risk of dropout. In a critical survey of 87 studies in LA / EDM, Gardner & Brooks (2018) found that several traditional research methods (such as descriptive, predictive, and explanatory models) are consistently being used to evaluate large-scale learning datasets in order to predict learners’ achievements, participation, and most commonly, persistence\(^5\). In relation to predictive and explanatory models, various techniques are proven to provide useful, comprehensible results. In order to predict learners’ performance, several LA / EDM studies have consistently preferred explainable predictive algorithms such as K-nearest neighbours (KNN) or the decision tree (Asif et al., 2017; Yehuala, 2015; Oskouei & Askari, 2014; Kabakchieva, 2013). The nature and relevance of algorithms, as well as algorithmic appropriateness, have been discussed further in Chapter 3, Section 3.4.

In recent EDM and LA predictive modelling work, there has been a greater focus on the learners’ characteristics and background. Extensive research in the last decade has utilized massive data resources from online learning to gain an insight into how learners’ various contextual variables (for example age, gender, education, or region of origin) may affect learners in attaining the different levels of achievements (see Joksimović et al., 2017; Robinson et al., 2016; Kuzilek et al., 2015; Kizilcec & Halawa, 2015; Greene et al., 2015; Wladis et al., 2014; Jiang et al., 2014; Romero et al., 2013). Likewise, other researchers have investigated the extent to which various demographic characteristics can potentially contribute toward successful learning outcomes and/or learners’ retention (Bozkurt & Aydin, 2018; Cen et al., 2016; Marbouti et al., 2016; Mueen et al., 2016; Huang & Fang, 2013).

For example, in the context of a blended learning environment, Tempelaar et al. (2015) compared more than 120 different data sources related to learners (e.g., demographics, prior education) and learning (e.g., behaviour in the virtual learning environment (VLE), successful assessment submissions) empirically amongst 922 business and economics undergraduate students. The study explicated the impact of a variety of attributes on learning outcomes. The attributes included educational background, entry test performance, learning disposition data, or VLE track data.

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\(^3\) The definition of learning analytics adopted this thesis is in line with the definition recommended by the Society for Learning Analytics Research (SoLAR), that is, “Learning analytics is the measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimising learning and the environments in which it occurs” (Ferguson, 2012, p. 3).

\(^4\) Educational Data Mining is considered a sub-field of data mining and concerned with “developing methods for exploring the unique types of data that come from educational settings, using those methods to better understand students, and the settings which they learn in” (Ferguson, 2012, p. 6).

\(^5\) This research operationalised persistence as the proportion of activities accessed before dropout (an approach mentioned by Singer, 2019; and used by Kizilcec et al., 2017; Reich, J., 2014 etc.).
Likewise, using the online learning setting at the Open University (OU), connected sets of studies have indicated that several predictors could be used to identify learners at risk (see, for example, Kuzilek et al., 2017; Hlosta et al., 2014; A. Wolff et al., 2014, 2013). The researchers analysed VLE data from OU courses and mapped learners’ behavioural patterns, for example, to predict performance drop (when performance fell well below the passing threshold) and the final outcome (i.e., pass or fail). Overall, they found that dynamic data extracted from the university VLE, when used along with learners’ contextual and demographic characteristics (such as gender, age, region of origin, and education), may significantly improve predictive modelling results. Along the same line, there are other large scale studies (for example, Kizilcec et al., 2017; Kuzilek et al., 2015; Wolff et al., 2014; Arnold & Pistilli, 2012) who employed one or more demographic characteristics amongst the predictors to understand learners behaviour, and advocated different measures such as early interventions or timely feedback generation to support at-risk students. Overall in the literature, academic achievements in blended or online learning settings have been modelled using a combination of various sources of information, both contextual and trace data (see Gardner & Brooks, 2018; Gašević et al., 2016).

Online learning environments provide educational researchers with voluminous data, both contextual and course engagement related. While contextual data have now been increasingly examined in extensive, systematic research (as highlighted by Bogarín et al., 2018; Winne, 2017; Joksimović et al., 2017), there is still a paucity in research exploring what aspects of demographic information are more relevant and important in understanding learners’ performance. Also, if certain demographic characteristics remain equally relevant throughout a course or their importance varies as a course progresses, it has received limited empirical attention. Nonetheless, several studies have highlighted an association between online learning outcomes and key demographic characteristics that may be critical to understanding online learners’ progression and retention, namely prior education (Allione & Stein, 2016; Wladis et al., 2014), age (Boyte-Eckis et al., 2018; Ke & Kwak, 2013), gender (Cai et al., 2017; Yukselturk & Bulut, 2009), disability (Cooper et al., 2016; Richardson, 2009), regional background (Bozkurt & Aydin, 2018; Z. Liu et al., 2016), and socioeconomic status (Diep et al., 2016; Wladis et al., 2014). This section further reviews the research for each characteristic in turn.

First of all, prior education has widely been recognised to strongly influence how learners perform in formal education (HEFCE, 2014). Research has found that prior education remains equally important in online learning (Kizilcec et al., 2017; Diep et al., 2016; Richardson, 2009). For example, Richardson (2009) found that “students with higher entry qualifications were more likely to obtain good degrees than students with lower entry qualifications”. Allione & Stein (2016) estimated the

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6 The same data sets were used in Study 1 (see Chapter 4) for the research presented here.
degree of interdependence between contextual characteristics (such as learners’ age, prior education, and gender) and course completion in a large MOOC (n = 35,819). Overall, they found younger college students to be more likely to abandon the course at an early stage relative to older students with little college experience.

Secondly, many studies have examined any potential link between learners’ age and academic achievements in blended and online learning but often offered contrasting results (Kizilcec et al., 2017; Diep et al., 2016; Richardson, 2013; Curşeu, 2013; Ke & Xie, 2009). For example, Ke & Xie (2009) examined data from adult learners enrolled in ten online courses from three different disciplines; nursing, business management, and education. Their study concluded that generally, for adult learners, online learning is more challenging to pursue. Interestingly, older learners reported higher satisfaction levels and self-reported good academic performance. However, in terms of performance prediction, age played an overall non-significant role (Ke & Xie, 2009). Diep et al. (2016) reported similar results in a study with 181 adult learners, whereby no substantial contribution of age to their predictive model was found. In contrast, Richardson (2013) found a small yet significant effect of age on distinct studying approaches using a large, age-stratified sample of 3,861 online learners. Nevertheless, several recent studies have recommended examining the role of age in online participation and achievement as a predictor, controlled or moderating variable (see, for example, Kizilcec et al., 2017; Diep et al., 2016; Richardson, 2013). As discussed earlier, examining the persistence in a large MOOC, Allione & Stein (2016) found that relatively older students (older than 35 years) were more likely to stay engaged with the course content.

Thirdly, over the past several years, gender differences in online participation and overall technology usage have been a subject of interest for many researchers (Cai et al., 2017; Diep et al., 2016; Nistor, 2013). In an educational context, a large body of literature can be found relating gender with academic achievements in online learning. Previous research has found that female learners demonstrate an overall behaviour of being relatively high achievers and were found to be more persistent and committed (McSporran & Young, 2001, Richardson & Woodley, 2003). While scrutinising the moderating influence of gender and location, Nistor (2013) analysed learners’ attitudes and participation in online courses of Psychology and Educational Sciences. With a sample of 156 graduate learners, the study reported significant gender differences in stability of attitude between male and female learners, with male learners exhibiting more stable attitudes (measured via questionnaire survey) and female learners exhibiting more stable participation (i.e., taking part in the course activities).

Apart from work exploring the moderating effect of gender, other recent studies (Kizilcec et al., 2017; Diep et al., 2016) used gender to predict the differences in the nature of course interactions
and learning participation. While evaluating other socio-demographic predictors (such as gender, age, and employment level), Diep et al. (2016) found gender as one of the most significant predictors of online interactions between learners and in help-seeking scenarios. Examining a questionnaire completed by 181 learners, the researchers identified female participants to be the keenest online learners. A similar result was noted by Kizilcec et al. (2017), who found that female participants in a course were relatively more inclined to contribute to social interactions and seek help than male participants. Despite the broad gender differences in course access and interactions, several studies report conflicting results as they found no significant or consistent relationship between gender and learning outcomes. For example, Yukselturk & Bulut (2009, 2007), found a strong link between age and technology competency or attitude towards online learning technology. Their results also indicated a significant contribution of gender (and age) when used in the equation of predicting success. These findings were in line with Greene and colleagues (2015) who found age to be associated with a decreased likelihood of dropout (i.e., greater likelihood of retention) in a large Coursera MOOC, but when used to predict achievement (operationalized as total exam grade or score) failed to achieve statistical significance. Notably, in earlier work on another large edX MOOC Breslow et al. (2013) also found no significant relationship between age, gender and learners’ achievement. In other words, the effect of gender and age on success in online learning mostly remained inconsistent and inconclusive.

A fourth factor potentially influencing student success is disability. As part of the registration process, learners are often given a choice to report a long-term physical, mental, intellectual, or sensory impairment. Such impairments are described under the umbrella term ‘disability’. One limitation attached with the approach of using a broad contextual characteristic like ‘known disability’ is that research findings may vary depending on the type of disability: learning difficulties (such as dyslexia), mental health problems (such as anxiety) or physical disability (such as hearing impairment). While a large number of learners may have been suffering from a known (or unknown) disability, systematic research on the impact of some kind of disability on online learning is still limited (Cooper et al., 2016). Previous research has reported mixed results regarding the influence of learners’ disability on online learning performance. For example, while analysing online learning barriers, with the help of data collected from 1,056 students, Muilenburg & Berge (2005) concluded that a significant number of learners experienced extensive prejudice due to their ethnicity, appearance, or disability in traditional higher education classroom settings, which then adversely affected their academic performance. When other studies in online or blended higher education examined the role of a known disability in learners’ academic success (for example, Jelfs &

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7 See https://help.open.ac.uk/browse/disability
Richardson, 2010; Richardson, 2009, 2015), they found no large statistical significance of disability as a predictor for learners’ achievement level.

In addition, to find the best predictors for learners’ attainment in a large sample of 103,950 graduates in the UK, Richardson (2009) suggested a combined effect of demographic characteristics significantly impacting and explaining considerable variation in educational attainment. However, the disability factor itself had a negligible effect, so learners with disabilities and learners with no known disabilities had almost equal chances of getting a good result in higher education if provided with the support needed. The above findings were consistent when this study was replicated amongst 1,085 online learners (65.5% disabled students) (Jelfs & Richardson, 2010). However, Cooper et al. (2016) cautioned that challenges experienced by disabled learners might be numerous and wide-ranging. Most of all, accessibility limitations in critical learning or assessment activity type may impede disabled learners from active participation and potentially negatively impact success in learning outcomes.

Fifthly, as evidenced by both global studies in online learning, as well as studies focused on geographical location within a particular country, there are strong regional and national factors that influence learners’ success (Cai et al., 2017; Allione & Stein, 2016; Guo & Reinecke, 2014). Similar observations have been repeatedly reported for financial, social, and/or psychological barriers in online learning in country-specific studies or those sampled for a particular region (Castaño-Muñoz et al., 2017; Kizilcec et al., 2017; Hansen & Reich, 2015). Moreover, recent work by Bayeck & Choi (2018) proposed that regional belonging may have a profound impact on online learners’ understanding and interpretation of images and content within learning resources. How learners’ region of residence may be linked with their performance merits far more elaboration. In this thesis, this contextual characteristic has been discussed further in section 2.5 below.

Finally, in addition to the geographic proximities, researchers found that the learners’ socioeconomic background may be one of the key deciding factors for learners’ withdrawal or retention from a course in an online or blended learning environment (Wladis et al., 2015; Richardson, 2009; Christie et al., 2004; Walpole, 2003). Since geographical belonging, ethnicity, and a region’s socioeconomic level may be related, Wladis et al. (2015) found socioeconomic status as a mediating variable with a strong linkage between ethnicity and online enrolment and performance. In their recent work, Kizilcec et al. (2017) found online learners from developed regions to be more persistent and perform significantly better than those from less developed regions. Probing the regional and socioeconomic variables as critical constructs in their work on implications of diversity in online learning spaces, Bozkurt & Aydin (2018) highlighted a significant disparity and noted that “most of the participation (in online learning) originates from developed,
Western, Anglo-Saxon cultures.” Section 2.5 discusses the significance of this contextual characteristic in more detail.

Overall, it has been evidenced empirically that characteristics such as nature of previous education (Castaño-Muñoz et al., 2017; Wladis et al., 2014), age range (Boyte-Eckis et al., 2018; Ke & Kwak, 2013), gender (Nistor, 2013; McSporran & Young, 2001), disability status (Jelfs & Richardson, 2010; Richardson, 2009, 2015), geographical location or country of residence (Bozkurt & Aydın, 2018; Z. Liu et al., 2016), and socioeconomic background (Stich & Reeves, 2017; Hansen & Reich, 2015), may have a predictive link with online learners performance. Previous work also evidenced that each of the attributes explained different parts of the variance in the outcome and, therefore, may have contributed to learning success differently. What has remained unclear is if several demographic characteristics are used collectively to predict learners’ performance, how does the relative importance of various demographic characteristics vary as the course progresses? Also, if this relative importance varies when the predictive modelling is performed on different courses from other disciplines? This background leads to the first two research questions in this thesis exploring inclusiveness in online learning. These two questions are addressed in Study 1.

**RQ 1.1** To what extent is there an association between learners’ demographic characteristics (i.e., Regional context, Socioeconomic context, Education, Age, Gender, and Disability) and online learning outcomes throughout the online course?

**RQ 1.2** To what extent does the association (from RQ 1.1) vary across different online courses with distinct learning designs?

Study 1 was conducted using publicly available data (i.e., the OU Learning Analytics Dataset (OULAD), (Kuzilek et al., 2017) and section 4.3.1 in Chapter 4. The data set selected for Study 1 consists of four online courses at the OU (n = 8581). In year 1 of the PhD, this particular public data set was used to explore the relative influence of the six demographic factors described above on study success while simultaneously applying and waiting for ethical approvals to use data from the OU online courses offered via the FutureLearn MOOC platform (section 3.5 presents ethical clearance from the OU ethics committee). By testing the methods described in Section 3.4 in the OULAD context while simultaneously applying for access to FutureLearn data, important lessons were drawn that were incorporated in the remainder of this PhD. Against the background that the MOOC learning environment will remain the focus of the rest of the three studies in this thesis, the next section explains the distinctive nature of the MOOC courses in the online learning landscape.

### 2.3 MOOC (MASSIVE OPEN ONLINE COURSE) LEARNING ENVIRONMENT

This section briefly presents several intrinsic features associated with MOOCs that enable them to support a large, diverse population of learners. The potential support for inclusiveness allows for a
spectrum of approaches, accounting for various languages, sociocultural settings, pedagogical strategies and technologies (Morgado et al., 2014). The formal definition proposed by Jansen & Schuwer (2015) of MOOCs encompasses the industry standards and guidelines, which have to be upheld for the course to be considered a ‘MOOC’. The definition, as discussed below, also explains MOOCs’ position in the broader development of online learning environments.

The term ‘Massive’ refers to a large number of learners who (are expected to) attend the course at a given time. The anticipated number is larger than a class size that can be taught in a formal/residential learning setting (i.e., approximately 150 students) (Jansen & Schuwer 2015). This level of scalability in a learning environment requires a learning design approach and pedagogical model in which academic facilities (such as tutoring staff and moderators or assessment evaluations) do not increase significantly when the number of enrolments increases.

The word ‘Open’ characterises ease in accessing the various learning resources from these courses. The term refers to minimal restraint on individuals willing to enrol in an online course, with no or minimal costs for participation. However, few restrictions on enrolment might still be in place, such as a particular prior education, technical skills, digital literacy level, academic pre-requisites, and location (Jansen & Schuwer 2015). The openness also indicates no discrimination in terms of technological features required to learn from the course material, for example, a specific browser or device requirements to access resources from a MOOC platform. Participants may still need a stable internet connection to get maximum benefits from the online learning resources, which leads to the following term discussed below.

The expression ‘Online’ denotes that all learning activities in a course can be accessed online, via the internet. That means the courses contain no obligatory offline, face-to-face, or blended activities. The learners can learn ‘in situ’, residing in their country of origin. Learners may still have an opportunity to attain local or international accreditation if provided with the course (e.g., credit hours towards a degree, verified certificate of completion, the relatively informal certificate of participation) (Jansen & Schuwer, 2015; Morgado et al., 2014).

Lastly, the term ‘Course’ refers to a pedagogical structure that makes MOOC a unit of study. For example, assuming MOOC as a unit of study means that the total study time or workload should be less than 1 ECTS (European Credit Transfer and Accumulation System), roughly equivalent to 25-30 study hours (Jansen & Schuwer, 2015; Morgado et al., 2014). To support inclusiveness and diversity in the MOOC learning environment, the researchers have recommended maintaining a variety in content types while stepping away from the predominantly video-based MOOCs. Nevertheless, understanding the word ‘course’ in MOOCs has been vastly negotiated in recent years. It potentially varies from one MOOC provider to another and from the higher educational sector to the commercial sector. Besides, the actual workload may differ from learner to learner and may be
dependent on several factors, such as the technical requirements, learners’ background knowledge, and other contextual factors.

Overall, these essential features of MOOCs facilitate learners with a mediated experience, i.e., fewer constraints for time, distance, prerequisites, or technological barriers. This structured informality makes MOOC learning environments unique and opens doors to potential diversity and scalability while supporting learners with different demographic characteristics. The research presented in this thesis explores if diversity is as prevailing in MOOCs as was initially expected (Shah, 2016; Pawlowski & Hoel, 2012) and how pedagogical settings (that is, learning designs) impact the way diverse learners engage with the various learning resources in these courses. Next, this chapter evaluates the role of various pedagogical factors in relation to online learners’ performance.

2.4 ONLINE LEARNING DESIGN

2.4.1 Learning Design at The Open University and FutureLearn

Outlining a learner’s learning experience is a complex problem. In his seminal work, Mayer (2005) stated that the overall learning experience comprises the active processes of filtering, selecting, organising, and integrating new information. While outlining the cognitive theory of multimedia learning, he stressed that learning content structure and presentation shapes ‘cognitive load’. His work suggested that (a) learning content presentation should have a coherent structure and/or (b) learners should be provided with enough guidance to build a cohesive structure for their learning. MOOC developers like FutureLearn, Coursera, and edX seem to consistently try to optimise the content structure and presentation to lessen the cognitive load for learners. These MOOC providers try to improve the learning experience and increase study success (i.e., persistence, engagement, and completion rates) by altering the information or task presentation and adjusting content type, difficulty, structure, length, or duration.

According to a widely accepted definition, multimedia learning occurs when learners learn through different presentations of learning material such as words (textual content), or pictures (static such as graphics, or dynamic such as videos) (Mayer, 2002). Previous work suggests that the most crucial step in multimedia learning is making a connection between text-based and visual-based representation of the learning information (that is, video, images etc.) (Mayer, 2005, p. 57). MOOC courses are often designed to attract more learners by making the acquisition of textual, visual and auditory information natural and easy for learners (Sergis et al., 2017; Rai & Chunrao, 2016; Margaryan et al., 2015). Furthermore, learners are expected to distribute their time to different learning activities to get the maximum (subjective) benefit within a limited time frame (Maldonado-Mahauad et al., 2018; Wigfield & Eccles, 2000). In terms of the course learning design, the structural

Interestingly, in relation to this connection, the research discussed in this thesis found distinct divide among geo-cultural and socioeconomic contexts (see Chapter 6 and 7 for more detail).
constructs (i.e., various types of learning activities and the sequence of those activities) must remain aligned with the respective learning objectives. Thus, in the rest of this chapter, I share some recent research in MOOCs that has observed a renewed interest in the various learning design aspects and temporal dynamics of learners’ engagement with learning activities. In the process, this research sought to unpack MOOC learners’ experiences with various learning design elements.

Next, this section further explains the learning design framework used in this research.

Learning design can be defined as designing a pedagogically informed structure of learning activities to support learners while remaining aligned with the curriculum. In a MOOC, learning design can provide a consistent way to map individual learning activities. The research in this thesis has theoretical groundings in the conceptual framework for Learning Design recommended by the OU Learning Design Initiative (OULDI) project (Cross, Galley, Brasher, & Weller, 2012). The same conceptual framework provided a foundation for the MOOC designs at the FutureLearn platform (Sharples, 2015), which is the primary source of MOOC data in this research. The formal taxonomy for OULDI, as shown in Table 2.1, was developed by Conole (2012), whose work describes learning design as a reusable, adaptable description or template which aims to make the structures of intended teaching and learning— the pedagogy—more visible and explicit thereby promoting understanding and reflection (see Cross & Conole, 2009). This taxonomy provides a way to abstract different learning activities in a meaningful way.

The framework categorises all learning activities as one of seven activity types; (1) Assimilative activities necessitate learners to participate in more ‘passive’ forms of learning like watching the video, (2) Finding and handling information activities require learners to interact with the information like drawing or analysing a graph, (3) Communication activities require learners to interact with each other for example participate in the course discussion forum, (4) Productive activities are promoting active forms of learning like constructing an artefact or making a project plan, (5) Experiential activities relate to the application of knowledge in a real-world setting, (6) Interactive/adaptive activities just like experiential activities require learners to apply their knowledge but in a simulated environment instead of real-world, and (7) Assessment activities refer to the activities designed to demonstrate knowledge and can be either formative, summative or self-assessment.
Table 2.1 Conole’s Learning Activity Profile. OULDI Learning design taxonomy used at the OU FutureLearn.

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

When a MOOC is designed, course instructors/designers estimate weekly workload, a rough estimation of the time duration a learner is expected to spend on a particular activity, e.g., 5 minutes to read an article (Sharples, 2015). The course activities are designed linearly (i.e., activity 3.4, followed by activity 3.5). However, the structure is generally planned in a way that activity navigation possibilities remain multimodal (that is, various navigation possibilities), whereby learners are only advised but not restricted to follow the course activities in a linear order. The syllabus and learning design guide designers to design a course, which can be reused in later course runs (see Figure 2.1). According to FutureLearn’s pedagogical strategy, the fundamental course element is called a step (see (Sharples, 2015) for a detailed discussion on FutureLearn MOOC learning designs). There are seven main types of steps; Article, Discussion, Peer Review, Quiz, Test, Video/audio, and Exercise (where Peer review is a composite step, consisting of Assignment, Assignment Review and Reflect). Most courses in FutureLearn comprise various combinations of five types of activities (i.e., Articles, Discussions, Videos, Discussions, Quizzes and Tests). However,
few courses may contain few Exercises and/or Assignments. FutureLearn recommends the design for 'storytelling'. Supporting the overall narrative, the course steps are assumed as ‘building blocks’, that are put together in different combinations to create the flow of activity that drives learning forward.

Figure 2.1 FutureLearn platform screenshot with course learning design features. The activity tags AR, VI, QU, and DI represent activity types Article, Video, Quiz, and Discussion.

The following text from FutureLearn Design guideline (Sharples, 2015) explains the design process.

"As an example, Week 1 of the Secret Power of Brands course starts with a video of people from around the world talking about the brands they love, to raise interest and show the scope of the course. Then learners are asked in a Discussion step what they want to get from the course. That is followed by a big question - "What is a brand?" - to motivate a sequence of videos to address the question from practitioners and academics. This leads on to a Discussion among the learners about how brands impact their world, and ends with a Test for learners to review their new knowledge, followed by short structured Articles on "Five ways to learn more" and "Our top 20 books to read on brand". The whole week is a narrative structure that motivates, questions, explains, discusses, reflects, and extends".

\[9\] Out of ten large FutureLearn MOOCs that were analysed in Study 3, only two course designs contained Assignments and four contained one or more Exercises. See Chapter 6 for more detail.
This example signifies the need to balance the assimilative, communication and assessment activities in the Week 1 storyline\textsuperscript{10}. The course structure at FutureLearn comprises a variety of activities (e.g., articles, discussion, videos etc.). Adopting the theoretical framework for LD discussed above, most FutureLearn courses offer a balance of assimilative, communication, and assessment activities.

This research specifically focused on three OULDI categories that represent the principal features. The three features are common in most FutureLearn MOOC designs (and in the designs of other large MOOC providers). First, Assimilative activities refer to learning activities that help develop, process, and attain information in an online course (e.g., reading articles or watching videos). Previously in his seminal work on multimedia learning, Mayer (2005) asserted how effective learning occurs when supported by multimedia, for example, words and visuals (i.e., article) and instructional videos. In fact, assimilative activities are key components of course designs.

Second, Communication-based activities allow learners to participate in course-related discussions. Compared to other large MOOC providers\textsuperscript{11}, FutureLearn follows a social-constructivist pedagogical style by promoting ‘learning through conversations’ (see Bearman et al., 2020; Manathunga et al., 2017; Ferguson & Clow, 2015). In FutureLearn MOOCs, discussion steps mimic a social media-style feed where learners can choose to start, like or comment on a discussion or follow their peers and instructors (Sharples, 2015). Various challenges may be associated with the facilitation of any large-scale deliberation (for example, short-lived participation, digital literacy where users may feel reluctant to engage with new technologies/features) (Ullmann et al., 2019). Despite this, FutureLearn was philosophically built on the grounds that working together collaboratively drives learning (i.e., socio-constructivist principles). Therefore, discussions are embedded explicitly in all courses making the MOOC a social learning space (Manathunga et al., 2017).

The third category focused on Assessments (Quizzes) – another known driver of learning. Assessment activities and the associated feedback facilitate knowledge acquisition and learning successes (e.g., Hattie & Timperley, 2007). Increased skills and learning successes, in turn, can motivate learners to persist in the course (e.g., Marsh & Craven, 2006). Overall, a typical FutureLearn MOOC structure comprises two types of assimilative activities (Video, Article), two types of assessment activities (Test, Quiz) and one communication activity (Discussion). All step categories remain available to learners for free, except Test. The assessment activity Test is only

\textsuperscript{10} As discussed later in this chapter, this research aims to follow the digital footprints of learners in this storyline and in the process, examine the differences across various geo-culture and socioeconomic contexts. The two consecutive studies in this thesis (Study 2 and 3; Chapters 5 and 6) evaluate learners’ engagement and then trace their dropout points within this storyline.

\textsuperscript{11} In terms of the number of enrolled learners, FutureLearn is the largest MOOC provider in Europe and the fourth-largest in the world (Shah, 2016).
available to ‘upgraded’ learners, i.e., learners who have upgraded their enrolment after paying a certain fee, potentially to obtain unlimited access to FutureLearn courses and a certificate. Unlike Quiz activity, which allows unlimited attempts, Tests allow a maximum of three attempts. Learners’ Test scores are then reported on the progress page and certificate transcript. It is worth mentioning that FutureLearn’s policy on the certificate of participation allows non-linear navigation through the activities. However, in most courses, a learner is required to mark as complete at least 50% of the course steps and attempt every test question to get a certificate of participation. Since open education remained the core focus of this research project, the MOOC studies examined freely accessible activities. Overall, for generalizability and possible replication across other MOOCs, this work primarily focussed on four freely accessible, most common learning activities across the FutureLearn MOOCs, i.e., Articles, Discussions, Videos and Quizzes.

The OULDI framework offers several advantages and strengths, such as reusability, adaptability, and abstraction of the overall course structure. However, the taxonomy has some limitations as well. First, it does not consider how long learners are expected to engage in an activity (duration or length). Second, it does not lead to clear, identifiable learning paths in terms of the sequenced activities learners are expected to follow (sequencing). However, these limitations do not limit designing instructionally successful, usable (and potentially reusable) learning activities at the OU or FutureLearn. In this research, these limitations do not impact the research design either. Moreover, the OULDI framework has been tested in several large-scale empirical studies (Holmes et al., 2019; Nguyen et al., 2017; Rienties et al., 2017).

According to Rienties (2021), the use of the OULDI model has resulted in an impact on the understanding, learning, and practice of 1541 university educators in over a dozen countries, including Belarus (Olney et al., 2020), China (Olney et al., 2021), Kenya (Mittelmeier, et al., 2018), South Africa (Greyling et al., 2020), and the UK by shaping their understanding and implementation of learning design, although not necessarily in FutureLearn courses. Therefore, this research used the OULDI taxonomy to investigate the cognitive and pedagogical features of FutureLearn MOOCs in relation to learners’ engagement and learning processes.

2.4.2 Learning Processes and Engagement in Learning Designs

Open-access learning environments attract people worldwide with a wide range of interests and learning objectives, which is reflected in the degree of participation and nature of engagement with the learning content (Milligan & Littlejohn, 2017; Kizilcec & Schneider, 2015). Possibly one of the most controversial debates in both residential and online education is how to define success in learning. Previous research has shown that participation levels and assessment outcomes alone do not constitute robust evidence of learning or academic success (Henderikx et al., 2017; Joksimović et al., 2017). Success and failure may be partly hidden in learners’ journeys through their respective
learning activities. While academic grades do not always evidence learning (Juhaňák et al., 2017; Jansen & Schuwer, 2015), the learning itself is *processual* and is guided by learners’ intentions. The processual nature of learning (in other words learning processes) may be observed and measured via interaction and engagement with various learning and assessment activities.

Learning interaction and engagement in online environments produce large volumes of data, irrespective of how a course has been designed. These data are produced from multiple sources, in a variety of formats, and with different levels of granularity (Romero & Ventura, 2013). The "trace data" or "clickstream data" stored in logs are typically captured within online learning environments at a very fine-grained level. This participation log data presumably can be considered as a set of silent, passive observations. The volume of data increases immensely as we move from general course-related details to learner-related information. The data size increases even more if we go deeper into each learner’s progress, from their learning sessions to individual learning activities accessed within those sessions (see Figure 2.2).

![Figure 2.2](image)

*Figure 2.2 Different levels of granularity and their relationship to the amount of data.*

*Source: (Romero & Ventura, 2013)*

Stored log data have no inherent meaning per se, as clicking may not necessarily reflect active engagement, let alone cognitive processing or learning (Winne, 2017). Indeed, Selwyn (2015) argued that the focus on these clicking data could lead to “dataveillance” and, perhaps more importantly, to a reductionist nature of the data-based representation of diverse learners. Nonetheless, Winne (2017) highlighted, these clicking data streams stored in logs, if used sensitively and sensibly, could provide essential insights into how some groups of learners are engaging in MOOCs, while others might not.
To date, only a relatively small fraction of that stored data have been explored in extensive, systematic MOOC research (Bogarín et al., 2018; Winne, 2017; Joksimović et al., 2017). Recent developments in the field of EDM and Educational Process Mining (EPM) have led to a renewed interest in research in understanding learning processes in a hybrid or MOOC learning environment (see, for example, Saint et al., 2021; Matcha et al., 2019; Saint et al., 2018). There is still a paucity in systematic research exploring what aspects of these data are relevant and valuable in understanding learning processes and how the relevance and usefulness vary between the various contexts (Winne, 2017; Sparke, 2017).

Emerging literature suggests that the structure, curriculum, and learning activity design within MOOCs have lately been topics of interest for both researchers and providers. The overall engagement in MOOCs has already been extensively studied, as it remains one of the largest concerns for major providers like Coursera, FutureLearn, and edX. In contrast, research on pedagogical aspects, and that with the potential to make MOOCs an inclusive learning environment, is still in its early stage (Bearman et al., 2020; Davis et al., 2016; Sergis et al., 2017). An average MOOC duration is four to six weeks, and learners’ dropout rate increases significantly after a couple of weeks (Shah, 2016; Jiang et al., 2014). Therefore, it has become even more critical to use the lens of learning designs to understand learning processes within the duration of limited time learners remain engaged and the nature of their engagement.

In related online learning literature, design aspects of the online learning environment have been found to influence learners’ engagement with different types of learning activities and their progression in a course (Nguyen et al., 2018; Rienties & Toetenel, 2016; Mangaroska & Giannakos, 2018; Davis et al., 2016). As discussed earlier in this chapter, learning design is the process of designing various types of learning activities informed by pedagogical structure and curriculum. Overall, course structure, duration, learning or instructional design, length and duration of course contents are some of the course-level factors that can potentially be altered to improve resource engagement and persistence. Given the processual nature of learning, one can investigate learning by measuring engagement in the form of detailed interactions with learning activities, such as reading material, instructional videos, assessments, and interpersonal exchanges, and then analysing learners’ progression through these activities (Davis et al., 2016; Maldonado-Mahauad et al., 2018).

Unlike face-to-face or blended learning environments, online courses are instrumented such that learner interactions are recorded in voluminous logs, offering an unprecedented granularity for studying learning at scale. Educational research on log-based behavioural modelling in Intelligent

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12 EPM deals with the applications of Process Mining techniques in the academic domain. See Section 3.4 in Chapter 3 for more detail.
Tutoring System (ITS), VLEs and MOOCs have found that log-based analyses can provide deeper insights into how learners engage and interact with different learning activities (see, for example, Bogarín et al., 2018; Sonnenberg & Bannert, 2015; Davis et al., 2016). However, despite increasing efforts to advance learning science research with log-based analyses in formal and blended learning environments, more research is needed to advance our understanding of learning processes and distinct activity engagement in open online learning (Bogarín et al., 2018; Juhaňák et al., 2017). Understanding any contextual differences in learners’ behavioural patterns and the temporal dynamics of their learning choices in the MOOC learning environment requires a comprehensive log data exploration. The term temporal dynamics used in this research has twofold meanings, the extent and duration of engagement and sequential progression through various activities. Apart from understanding the similar or dissimilar learning processes or sequences in MOOCs, another critical aspect worth exploring is the relative frequency of access for each activity type. Another way to recognise learners’ interests in different learning activities is to analyse the relative frequency of access that signifies typical learners’ experiences with the respective activities (Davis et al., 2017; Z. Liu et al., 2016). In particular, it may represent general experience when estimated for an entire cohort.

Online learning designs may comprise various types of learning activities set in a predetermined order. Within formal online learning contexts, the impact of learning designs on learners' behaviour, satisfaction, and learning outcomes has been widely acknowledged (Rienties & Toetenel, 2016). Likewise, Nguyen et al. (2017) found preliminary support for the impact of learning design on learners’ online engagement. They noted that "learning design could explain up to 60% of the variance of the time spent on learning platform". However, most of the research on learning design focused on measures of learning that are not processual (Mangaroska & Giannakos, 2018). For example, the impact of learning designs on learning outcomes or overall engagement has been analysed (see Mangaroska & Giannakos, 2018), but generally without considering the manner in which learners progress in a course.

While early research on MOOCs focused more on understanding the various summative measures like completion rates and final course grades (Li & Baker, 2018; D. Davis et al., 2017), more recent work has examined how learners are moving through the course content as a way of understanding the learning process itself (Saint et al., 2021; Bogarín et al., 2018). To advance our understanding of learner behaviour, several studies have been using clustering approaches to identify learner subpopulations based upon their overall resource-engagement behaviour (Li & Baker, 2018; Ferguson & Clow, 2015; Kizilcec et al., 2013), and more recently, sequence-mining techniques to identify common engagement sequences that may reflect learning processes (see, for example, Davis et al., 2018; Guo & Reinecke, 2014; Saint et al., 2021; Matcha et al., 2019; Saint et al., 2018).
In order to understand learning processes in MOOCs, findings from most of these studies suggest that it helps to first group learners based on their general behavioural profile to reduce variance due to different enrolment intentions and then to examine fine-grained interaction processes with the learning activities (the approach has been discussed further in Chapter 5 section 5.1 and 5.2). While these sequence/process-mining techniques have provided important insights into how different groups of learners engage in MOOCs, some researchers have argued that these approaches need to be embedded in strong learning science principles (Mangaroska & Giannakos, 2018; Winne, 2017).

Therefore, this research builds upon the existing literature from learning sciences and aims to explore the linkage (if any) between activity types in a MOOC LD, learners’ interests (i.e., expressed through the relative frequency of access), and processual learning (i.e., learners’ progress in time). Study 2 in this thesis has investigated and compared the most dominant progression and activity access frequencies. While examining the temporal dynamics in MOOC learning processes, Study 2 takes into account the grouping of learners based upon their inclination towards certification (see Chapter 5, sections 5.1 and 5.2 for more detail). This study in this dissertation sought to answer the following specific research questions.

**RQ 2.1** How and to what extent does engagement with different learning design elements (i.e., (a) assimilative learning activities (e.g., articles, videos), (b) communication activities (e.g., discussions), and (c) assessment activities (e.g., quizzes)) differ between learners?

**RQ 2.2** How and to what extent do temporal learning paths (i.e., sequences of learning activities) differ between learners?

While Study 2 examined the engagement differences across various activities, Study 3 in this thesis sought to quantify the link between various learning activities and the extent to which learners stayed engaged in a course. Against this background, and guided by the questions (RQ 2.1 and RQ 2.3), the subsequent Study 3 evaluates and quantifies the link between the various number of learning design elements in a course and how long a learner engages or persists in that course, raising the following specific question addressed in Study 3:

**RQ 3.1** How and to what extent does the number of learning design elements (i.e., (a) assimilative learning activities (e.g., articles, videos), (b) communication activities (e.g., discussions), and (c) assessment activities (e.g., quizzes)) in a course predict learners’ persistence?

**2.5 GEO-CULTURAL AND SOCIOECONOMIC CONTEXTS AND LEARNING PERFORMANCE**

In the context of the online learning environment, the critical role of learning design in learners’ engagement has been widely acknowledged. Prior research (discussed in section 2.2) has also linked other contextual factors with the engagement behaviours in MOOCs. Such contextual features
include broader regional, geo-cultural backgrounds, as well as the socioeconomic status of the learners’ region of residence. A recent analysis of all edX MOOCs offered between 2012 and 2018 (565 iterations of 261 different courses) reported a global gap in enrolment and certification (Reich & Ruipérez-Valiente, 2019). It was found that in most MOOCs, relatively more engaged learners originated from affluent countries and neighbourhoods. Still, limited research has explored the variation in engagement with different activity types in a MOOC learning design and how such variation varies between the geo-cultural and socioeconomic contexts. With an increase in the number of MOOC enrolments worldwide, there is a need to design MOOCs that are inclusive and diverse as the courses need to evolve to truly reach their aim of mass education. Therefore, Section 2.5 aims to provide an account of the potential link between learners’ online performance and their socioeconomic, geographic, or geo-cultural contexts.

Culture, often defined as ‘collective complexes of learned behaviours and perceptions of individuals in a society’ (Tylor, 1871), influences how an individual processes and interprets information. Therefore, education cannot remain disconnected from the cultural values of a society. The term ‘culture’ itself is multifaceted. The related term “geo-culture” used in the title was proposed by Wallerstein (1991) in an analogy with geopolitics. This term was initially suggested with a mention that it does not represent something “supra-local” or “supra-national” but a representation of the cultural framework within which the world system operates. The concept of geo-culture often helps researchers to outline how people receive and process new information. The term is often employed in theoretical frameworks to explain how people act, behave and learn based on their geographical location or area of origin. The next section briefly discusses several conceptual frameworks that many researchers have considered worthy of scholarly attention.

### 2.5.1 Conceptualization of Geo-Culture

There are conceptual frameworks that have received considerable attention from researchers investigating the relationship between learning and various cultural dimensions. Few of the most established frameworks are briefly discussed in this section. For example, among other frameworks, Hall and Hall (2001) highlighted the importance of context in any culture. They used a contextual perspective to categorise countries based on communication features common in the countrymen. It was suggested that implicit or explicit communication or social patterns, in any culture, can be distinguished as High context and Low context.
Table 2.2 Characteristics of Hall’s High context vs Low context cultures (Source: Hall and Hall (2001)).

<table>
<thead>
<tr>
<th>High Context</th>
<th>Low Context</th>
</tr>
</thead>
<tbody>
<tr>
<td>Indirect and implicit messages</td>
<td>Direct, simple and clear messages</td>
</tr>
<tr>
<td>Polychronic</td>
<td>Monochronic</td>
</tr>
<tr>
<td>High use of non-verbal communication</td>
<td>Low use of non-verbal communication</td>
</tr>
<tr>
<td>Low reliance on written communication</td>
<td>High reliance on written communication</td>
</tr>
<tr>
<td>Use intuition and feelings to make decisions</td>
<td>Rely on facts and evidence for decisions</td>
</tr>
<tr>
<td>Long-term relationships</td>
<td>Short-term relationships</td>
</tr>
<tr>
<td>Relationships are more important than schedules</td>
<td>Schedules are more important than relationships</td>
</tr>
<tr>
<td>Strong distinction between in-group and out-group</td>
<td>Flexible and open</td>
</tr>
</tbody>
</table>

This research work categorised the following regions/countries: German, Swiss-German, English, French, North American, Scandinavian (except Finland), Italian, Latin American, Japanese, Arabic. Table 2.2 summarises the characteristics of both types of cultures using the respective communication parameters. Figure 2.3 presents a brief comparison of High context versus Low context cultural differences based on the contextual differences between various nations.

Another important categorisation is based upon Hofstede’s National Cultural Dimensions (NCD), about how values in the workplace are influenced by national culture (Hofstede, 1980). The categorisation was based upon several connected studies on how values in the workplace are influenced by national culture (Hofstede, 1980). The original work comprised more than 117,000 survey results from 66 countries (though the sample mainly drew from IBM). Since then, the research has been revisited and updated many times (Hofstede & McCrae, 2004; Hofstede, 1994, 2011). Hofstede’s NCD contained six dimensions that have been used to explain cross-cultural differences in different regions. The proposed cultural dimensions are as follows: (1) Power
Distance, (2) Uncertainty Avoidance, (3) Individualism/Collectivism, (4) Masculinity/Femininity, (5) Long/Short Term Orientation, and (6) Indulgence/Restraint. (See Figure 2.4 for more detail).

<table>
<thead>
<tr>
<th>Cultural Dimension</th>
<th>Small Power Distance</th>
<th>Large Power Distance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Use of power</td>
<td>Power is a basic fact of society and should be used wisely</td>
<td></td>
</tr>
<tr>
<td>Parents treat children as equals</td>
<td>Parents teach children obedience</td>
<td></td>
</tr>
<tr>
<td>Affirmation of tradition</td>
<td>Older people are respected and should be treated with respect</td>
<td></td>
</tr>
<tr>
<td>Tolerance of deviant persons</td>
<td>Higher education and well-being</td>
<td></td>
</tr>
<tr>
<td>Religions stressing equality of believers</td>
<td>Religions with a hierarchy of priests</td>
<td></td>
</tr>
</tbody>
</table>

Weak Uncertainty Avoidance | Strong Uncertainty Avoidance
---|---
The uncertainty inherent in life is accepted and each day is taken as it comes | The uncertainty inherent in life is felt as a continuous threat that must be fought |
Ease, lower stress, self-control, low anxiety | Higher stress, irritability, anxiety, sociability |
Higher scores on subjective health and well-being | Lower scores on subjective health and well-being |
Intolerance of deviant persons and ideas what is different is dangerous | Intolerance of deviant persons and ideas what is different is dangerous |
Need for clarity and structure | Need for clarity and structure |
Teachers supposed to have all the answers | Teachers expected to be able to answer all questions |
| | Staying in jobs even if disliked |
| | Emotional need for rules, even if it is is not obligatory |
| | In politics, citizens feel and are seen as competent towards authorities |
| | In religion, philosophy and science: belief in ultimate truths and grand theories |

Individualism | Collectivism
---|---
Everyone is supposed to take care of themselves or their immediate family only | People are born into extended families or clans which protect them in exchange for loyalty |
"I" consciousness | "We" consciousness |
Right of privacy | Stress on belonging |
Speaking one's mind is healthy | Harmony should always be maintained |
Others classified as individuals | Others classified as in-group or out-group |
Personal opinion expected: one person, one vote | Opinions and results predetermined by in-group |
Protest against norms lead to guilt feelings | Transgression of norms leads to shame feelings |
Linguistic in which the word "I" is indispensable | Languages in which the word "I" is the only one |
Purpose of education is learning how to learn | Purpose of education is learning how to do |
Task prevails over relationship | Relationship prevails over task |

Femininity | Masculinity
---|---
Minimum emotional and social role differentiation between the genders | Maximum emotional and social role differentiation between the genders |
Men and women should be modest and caring | Men should be men and women may be assertive and ambitious |
Balance between family and work | Work prevails over family |
Admiration for the weak | Admiration for the strong |
Both genders and men share the same facts and feelings | Fathers deal with facts, mothers deal with feelings |
Both boys and girls may cry if they are not treated fairly | Girls cry, boys don't; boys should fight back, girls should not fight |
Mothers decide on the number of children | Fathers decide on family size |
Many women in elected political positions | Few women in elected political positions |
Religion focuses on human beings | Religion focuses on God or gods |
Moralistic attitudes about sexuality; sex is a way of relating | Moralistic attitudes about sexuality; sex is a way of performing |

Short-Term Orientation | Long-Term Orientation
---|---
Most important events in life occur in the past or take place now | Most important events in life will occur in the future |
Personal status and stability is a good person is always the same | A good person adapts to the circumstances |
There are universal guidelines about what is right and wrong | What is right and wrong depends on the situation |
Traditions are sacrosanct | Traditions are adaptable to changing circumstances |
Family life guided by emotions | Family life guided by shared tasks |
Services to others is an important goal | Trying to learn from other countries |
Social spending and consumption | Thrift and perseverance are important goals |
Students succeed in academic settings | Large savings, more funds available for investment |
Students attribute success to effort and to lack of effort | Students attribute success to talent and effort |
Slow economic growth of poor countries | First economic growth of countries to be at a level of prosperity |

Indulgence | Restraint
---|---
Higher percentage of people declaring themselves very happy | Fewer very happy people |
A perception of personal life control | A perception of helplessness: what happens to me is not my own doing |
Freedom of speech is an important | Freedom of speech is not a primary concern |
Higher importance of leisure | Lower importance of leisure |
Less likely to remember positive emotions | Less likely to remember positive emotions |
In countries with educational opportunities, higher birth rates | In countries with educational opportunities, lower birth rates |
More people actively involved in sports | Fewer people actively involved in sports |
In countries with enough food, fewer obese people | In countries with enough food, fewer obese people |
In wealthy countries, stricter sexual norms | In wealthy countries, stricter sexual norms |
Higher number of police officers per 100,000 population | Higher number of police officers per 100,000 population |

Figure 2.4 Hofstede’s National Cultural Dimensions (NCD) (Source: Hofstede, 2011)

It is necessary to acknowledge here that the cultural dimensions and parameters proposed by rigorous efforts of Hall and Hall (2001) and Hofstede (1980) are well-established and equally well-cited. But they are now frequently criticised for putting small efforts to generalise the findings to
extend to a global scale (a limitation that can be noticed in Figure 2.3). They are especially archaic in utilising merely geographical borders as boundaries for cultures (Würtz, 2005). Hofstede's NCDs have been extensively used in various sectors worldwide and have remained a standard in business textbooks and cross-cultural research for a long time. However, extending Hofstede's work, the GLOBE study (House et al., 2004) provided a fresh perspective.

The GLOBE research program was initially proposed to understand societal and organisational effectiveness in the cross-cultural work environment (House et al., 2004). Around 170 researchers participated in this global, large-scale research, which resulted in nine cultural dimensions altogether. The GLOBE study and its nine dimensions can presumably be called an extension of Hofstede's work as it was based on other research in culture and drew heavily from Hofstede (1980) as well as from 'Need Theory' by McClelland (1985). The Need Theory (sometimes called Three Needs Theory) is a motivational model that explains how 'the needs for achievement, power, and affiliation' affect the actions of individuals (McClelland, 1985). It suggests that individuals' motivations are driven by their life experiences and the opinions of their culture. The theory further explained that when individuals are driven by their 'need for achievement', they prefer moderately difficult tasks, like to see the results of their efforts, wish to receive feedback, etc. Overall, they remain well-motivated by accomplishments. Whereas individuals with a 'need for affiliation' create and maintain social relationships, prefer working in groups and adhere to the culture's norms. Such individuals choose collaboration over competition. Finally, people who value discipline embrace competition but enjoy status recognition, winning arguments, and influencing others. Such individuals are motivated by their 'need for power' to thrive for a better personal status (McClelland, 1985). It is noteworthy here that the Need theory is primarily a motivation theory but has been widely used in conceptual cross-cultural research. McClelland (1985) himself has stated that life experiences and cultural background largely influence individuals' motivations. (Figure A 2.1 in Appendix A explains how each of the GLOBE dimensions was built upon related work from the past).

As discussed briefly before, for cross-cultural management, House et al. (2004) empirically devised the following ten cultural clusters (often called GLOBE clusters): Anglo-Saxon, Latin Europe, Nordic Europe, Germanic Europe, Eastern Europe, Latin America, Sub-Saharan Africa, Middle East, Southern Asia and Confucian Asia (see Figure 2.5). Following is a summary of GLOBE cultural dimensions (source: Hadwick, 2011).

**Power distance** – the extent to which individuals expect equality in power distribution.

**Uncertainty avoidance** – the extent to which social norms, regulations, and procedures are relied on to reduce future uncertainties.
Humane orientation – the extent to which society rewards individuals for fairness, altruism, and humane behaviour towards others.

Collectivism – the extent to which institutions encourage collective action and distribution of resources (i.e., institutional collectivism). Also, the extent to which individuals are exclusively loyal to their institutions or families (i.e., in-group collectivism).

Assertiveness – the extent to which individuals are aggressive in their relationships with other individuals and institutions.

Gender Egalitarianism – the extent to which society minimises gender inequalities.

Future Orientation – the extent to which the individuals delay instant gratification activities and invest for the future.

Performance Orientation – the extent to which society encourages and rewards excellence in performance or the effort to achieve such excellence.

Figure 2.5 Example of country categorisation from GLOBE study
The GLOBE project gained considerable support due to the scope, depth, duration, and overall methodological sophistication it offers. However, like any theoretical framework, GLOBE has its limitations. It was later found that for seven of the nine dimensions, the societal practices (as things are) and societal values (as things should be) were negatively correlated (Brewer & Venaik, 2010). This aspect has been particularly criticised by other researchers as well (Hofstede, 2006). One commonly hypothesised reason for the negative correlation between practices and desired values is that values may be viewed from a position of deprivation (for example, a typical response, ’I want low Power Distance because I live in a society with high Power Distance’). This reasonable proposition still leaves a door open for interesting future research that is out of this research scope.

It has widely been argued that added complexity in the GLOBE model offers a broader global scope, is essentially based upon Hofstede's ideas. The stated complexity introduces a fine-grained look into cross-cultural research in a theory-based and geo-centric manner (Mensah & Chen, 2013; Hadwick, 2011). Still, researchers may find consistent differences across the GLOBE cultural clusters about religion, official language, ethnicity, regions of the world, and especially native language groups (for example, Niger-Congo, Austronesian, Uralic) (Mensah & Chen, 2013). These inconsistencies were partly addressed in follow-up work; an extension is discussed as follows.

The extension of GLOBE societal clusters (Extended-GLOBE) by Mensah & Chen (2013) can be considered a significant milestone towards a relatively comprehensive and overarching nation-culture categorisation. The groupings were based on empirical cultural dimensions obtained from the individual country's surveys in previous studies. Thereby, including additional countries using similar methodology required similar survey data from those countries, which was difficult if not impractical. This hardship in obtaining comparable data has prevented cultural grouping from being extended to the remaining countries beyond those initially included (Mensah & Chen, 2013).

From an anthropological psychology standpoint, Woliver & Cattell (1981) have provided details on factors contributing to similarity (or dissimilarity) of cultural practices. The research suggested using historical (such as colonial background or other historical belonging), geographical features (i.e., neighbouring regions), religious and socioeconomic factors to classify countries into cultural clusters. Furthermore, language is a tool that is mainly used to communicate and maintain a culture by containing and conveying cultural values (Bozkurt & Aydin, 2018). Therefore, language (both official and native) can also be considered an important cultural feature. Referring to Woliver & Cattell (1981), there is also incontrovertible evidence that primary cultural practices differences are correlated with ethnicity and geographic nearness. However, this discussion is out of the scope of this research.
Using an approach driven by the literature discussed above, the Extended-GLOBE research assumed that 62 countries in the original GLOBE were archetypal. The study assumed that those countries/regions were representative of all countries worldwide and hence can be used to devise an empirical model. Also, there is a possibility to extend the inferred cultural dimensions to other countries not included in the original study. Instead of using survey data (like the original GLOBE), the Extended-GLOBE study used quantitative data (and methods) for the updated countries' clustering. Following five main variables were perceived to be necessary to define culture in external terms: (1) racial/ethnic distribution; (2) religious distribution; (3) world region or geographic proximity; (4) major language distribution; and (5) (British) colonial heritage (Mensah & Chen, 2013). Table A2.1 in Appendix A provides an overview of the variables used in the statistical model for Extended-GLOBE modelling. The data on religion, official languages, and ethnic and religious distribution within a country were gathered from the latest CIA World Factbook, Wikipedia.com (if properly sourced), and individual country's official websites (if needed for cross-checking). Finally, data on the relative population of a country speaking a particular language (or language group) were gathered from the Web version of Ethnologue: Languages of the World (Lewis, 2009). The latitude and longitude of the capitals of the countries were used to measure geographic proximity.

Using these variables for individual countries, the Extended-GLOBE study applied multivariate discriminant analysis on original GLOBE countries. It then extended the categorisation to the holdout sample (rest of the countries worldwide, i.e., those never categorised before). Based on the degree of fit of the statistical model (discriminant analysis), all other countries were classified into the ten cultural clusters identified in the original GLOBE study. Nevertheless, the research provided findings based on statistical modelling that "future researchers using survey techniques can either refute or confirm" (Mensah & Chen, 2013).

Researchers often use various conceptual frameworks to understand cross-cultural differences in learners' perspectives (see, for example, Baker et al., 2020; Kizilcec & Cohen, 2017; Mensah & Chen, 2013a; Joy & Kolb, 2009). In order to understand how learners from different geo-cultural regions worldwide engage with learning activities, this PhD research used Hofstede’s National Cultural Dimensions (NCD) (Hofstede, 1980), along with extended GLOBE (House et al., 2004) (except for Study 1 which examined UK based learners’ data). Section 3.3 in the methodology chapter provides several rationales behind selecting the two linked conceptual frameworks.

The set of frameworks used to understand the experiences of diverse learners originating from dissimilar geo-cultural contexts characterises a comprehensive view of global regions and cultural constructs in those regions. This research primarily draws upon two dimensions commonly used in learning sciences; (i) Power Distance (PD) Index and (ii) Individualism/Collectivism. The ten geo-
cultural groups listed above were further divided into simplistic subgroups: one with high PD and the other with low PD, similarly one subgroup with a high collectivism score and the other with more individualist (see Table 2.3). Several rationales for opting for these two dimensions are shared later in this chapter.

Table 2.3. Geo-cultural regions categorisation based on the region’s median score in two NCD dimensions; Power Distance Index and Individualism/collectivism.

<table>
<thead>
<tr>
<th>Cultural dimension</th>
<th>Geo-cultural region</th>
</tr>
</thead>
<tbody>
<tr>
<td>Power Distance</td>
<td>High Power Distance</td>
</tr>
<tr>
<td></td>
<td>Sub-Saharan Africa (AF), Confucian Asia (CA), Eastern Europe (EE), Latin America (LA), Latin Europe (LE), Middle East (ME), Southern Asia (SA)</td>
</tr>
<tr>
<td></td>
<td>Low Power Distance</td>
</tr>
<tr>
<td></td>
<td>Anglo-Saxon (AS), Germanic Europe (GE), Nordic Europe (NE)</td>
</tr>
<tr>
<td>Individualism</td>
<td>High (Individualist)</td>
</tr>
<tr>
<td></td>
<td>Anglo-Saxon (AS), Germanic Europe (GE), Nordic Europe (NE), Latin Europe (LE)</td>
</tr>
<tr>
<td></td>
<td>Low (Collectivist)</td>
</tr>
<tr>
<td></td>
<td>Sub-Saharan Africa (AF), Confucian Asia (CA), Eastern Europe (EE), Latin America (LA), Middle East (ME), Southern Asia (SA)</td>
</tr>
</tbody>
</table>

A vast body of research has analysed the natural link between culture and education (e.g., Bozkurt & Aydin, 2018; Arnove, Torres, & Franz, 2012) and found that the design and content of the curriculums and classroom practices in formal education, for example, maybe explicit in various cultures and regions. The research also suggested that learners’ experiences and reactions to their education are partly grounded in, and shaped by, the culture and the region they belong to. Studies conducted in global or in specific regions have evidenced that various regional, national, and cultural factors influence enrolment (Wladis et al., 2015) and success (Cai et al., 2017; Guo & Reinecke, 2014) in online learning.
For example, Wladis et al. (2015), found a strong linkage between ethnicity and online enrolment. The disparity that left learners from a Hispanic and Black ethnic background, for example, to be significantly underrepresented, was reflected in lower enrolment rates of learners from both ethnicities, whereby both ethnicities were significantly less likely to study STEM major courses online. Overall their findings were aligned with Stich & Reeves (2017), who examined various socio-demographic characteristics (such as socioeconomic status, race/ethnicity) of MOOC learners and found ‘significant disparities’ for some ethnic and racial minorities throughout the US (racial inequalities in online learning merit more research. This interesting future direction has been discussed further in the final chapter in this thesis).

Numerous studies have employed countries’ scores from Hofstede’s NCD to explore the relationship between cultural diversity in the learners' population and learners’ interactions and participation in formal, blended and online settings (Ogan et al., 2015; Guo & Reinecke, 2014; Tempelaar et al., 2013). In a cross-cultural study, Ogan et al. (2015) analysed learners’ possible off-source help-seeking inclinations in computer-assisted learning. This large-scale research was conducted in three different cultures in three countries (i.e., The US, Philippines, and Costa Rica). A tutoring software was used to help and assist learners with graph plotting. The learners’ log data, and post-test results suggested distinctive cultural differences in help-seeking behaviour, collaborative learning, and interclass competition. It turned out that different cultural dimensions, such as individualism played an essential role in varied help-seeking or collaborative behaviours.
In recent work, Bayeck Choi (2018) focused on introductory videos from three MOOCs. They found that culture influences learners’ understanding and interpretation of images and content. The researchers used cultural dimensions of Power Distance Index (PDI), Individualism (IDV) vs Collectivism and Masculinity vs Femininity to compare MOOC introductory videos developed by three countries from three different continents (i.e., France, South Korea, and The US). It was found that the MOOC introductory videos were highly influenced by, and were illustrative of, the cultural dimensions of the countries they were produced (Bayeck & Choi, 2018). Various other cultural dimensions were also used to unpack the cultural importance in learning. For example, the contrasts in high-context versus low-context cultures have been instrumental in explaining social relationships individuals develop or maintain in MOOC learning environment (Gaisch & Jadin, 2014; Jadin & Gaisch, 2014). All in all, there is emerging evidence that geo-culture has an influence on how people learn online, and in MOOCs in particular. However, to the best of my knowledge, no systematic large-scale study has examined the combined influence of geo-culture and learning design on learners’ persistence. My research presented a way to quantify this interaction and hence offered an interesting and unique contribution to the existing body of knowledge.

2.5.2 Conceptualization of Socioeconomic Context

Finally, as previously eluded in section 2.2, several studies have shown that socioeconomic context may play an important role in how learners engage in MOOCs, and whether (or not) they are able to successfully complete a MOOC (Reich & Ruipérez-Valiente, 2019; Kizilcec & Halawa, 2015; Wladis et al., 2015). In terms of socioeconomic grouping, there are numerous possible ways to group learners. For example, a frequently used categorisation uses Human Development Index (HDI) quartiles to divide countries into four HDI groups; Very high, High, Medium, and Low HDI groups. HDI is a composite measure of achievements in three basic dimensions of human development: a long and healthy life, access to education, and a decent standard of living (see Figure 2.7 for more detail). For ease of comparability, the average values of achievements in these three dimensions are put on a scale of 0 to 1, where a greater score is better. These indicators are then aggregated using geometric means. A country is categorised in the very high group if its HDI value lies in the top quartile or the high group if its HDI lies in percentiles 51–75. Countries in the medium group have HDI values in percentiles 26–50. Finally, a country is in the low group if its HDI is in the lowest quartile. Another similar categorisation also uses the measure of HDI but instead divides countries into two groups: developed countries and developing countries (Klugman, 2010). The countries with the HDI score ‘very high’ are referred to as developed, and countries not in this group are called

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13 This framework used contextual perspective to categorize countries into groups based on communication features common in the countrymen, see Table 2.2.

14 For more detail, see: http://wwwhdrundporgsitesdefaultfilesreports270hdr2010en_complete_reprintpdf
developing. However, the categorisation into two groups seems too coarse to be used for analytical purposes.

One more closely linked but slightly less known socioeconomic categorisation uses Multidimensional Poverty Index (MPI) (Klugman, 2010). Identical to HDI measure in nature, MPI, by definition, is a measure of severe deprivations in the dimensions of health, education, and living standards that combines the number of deprived and the intensity of their deprivation. Like development, poverty can be multidimensional. Therefore, MPI can also be considered a multidimensional measure of poverty. This index identifies deprivations across the same three dimensions as the HDI. It shows the number of people who are poor (suffering a given number of deprivations) and the number of deprivations with which poor households typically contend (Klugman, 2010). Table A2.2 in Appendix A summarises these three socioeconomic classification schemes.

![Figure 2.7 Components of Human Development Index (HDI); Three dimensions and four indicators. (Source: (Klugman, 2010))](image)

One other, though very similar alternative to the HDI score, is gross national income (GNI) per capita which is also often used to measure the standard of living in the respective country. Based upon a country’s economic prosperity indicated by GNI thresholds, the World bank has divided world economies into four groups: High income, Upper middle income, Lower middle income, and Low income. As for the income level for each economy, the values from local currency are converted to US dollars. This categorisation was initially proposed in 1989, whereby the threshold was based mainly upon the previously established operational threshold. The method used to identify the income thresholds accounts for three-year exchange rates adjusted for inflation. Therefore, it lowers the potential impact of exchange rates and abrupt changes in currency values. Figure 2.8 illustrates the overall changes in the aggregated income threshold for the years between 1990 and 2019.
In terms of population distribution, the share of the world population living in Low income societies has decreased significantly during the last two decades, perhaps due to considerable economic growth during this period (see Figure 2.9). Overall, around 15.9% world population currently lives in a society categorised as High income, compared to 35% in the Upper middle and 39.8% in Lower middle-income societies. Still, around 9.3% of the world population lives in one of the Low-income countries. Figure 2.10 shows the categorisation on a world map.
In the literature, there seems to be an emerging narrative of a global divide in the way learners engage with various elements of learning designs in the MOOC learning environment. For example, in a systematic analysis of attrition and performance in 20 MOOCs (n = 67,333), Kizilcec & Halawa (2015) discussed a significant gap in MOOC learners’ participation resulting from factors such as geographic location (based on learners’ IP addresses), average neighbourhood household income, motivation accompanied by self-regulatory skills, and social integration (that varies between
different cultures and regions). These researchers found learners from African, Asian, and Latin American countries to be less persistent in accessing course resources and exam material. The researchers also found that compared to learners from Europe or North America, learners residing in the regions listed above were less likely to achieve grade milestones in their respective courses. In a follow-up study, Kizilcec, et al. (2017), again found a wide MOOC retention and completion gap between less developed (LDC) and more developed countries (MDC), which recurrently points to the potential association between socioeconomic context and online learning performance. When observing the enrolment and completion gaps in all edX courses (offered between 2012 and 2018), other recent work also reported consistent disproportionate participation from affluent countries. Whereby most enrolled and certified learners belonged to one of the very high HDI categories and lowest rates of enrolment and certification were noticed for low HDI category (Reich & Ruipérez-Valiente, 2019). Similar observations have been repeatedly reported for financial, social, or psychological barriers in MOOC learning in country-specific studies or those sampled for a particular region (see, for example, Castaño-Muñoz et al., 2017; Kizilcec et al., 2017; Hansen & Reich, 2015). Overall, several other researchers have found identical evidence for significant disparities linked with attributes such as ethnicity and race (Stich & Reeves, 2017; Wladis et al., 2015), average neighbourhood household income or the national Human Development Index (Kizilcec, et al., 2017; Hansen & Reich, 2015), and level of social integration (Kizilcec, et al., 2017; Z. Liu et al., 2016).

While analysing a large sample (n = 29,149) enrolled in a famous interdisciplinary MOOC, Liu and colleagues (2016) also observed a clear divide. For instance, the researchers noticed a clear distinction between learner’s test-taking behaviour and their discussion forum participation when they compared mainly English-speaking, prosperous, low power distance, individualist countries (such as Australia, Canada, the US, and UK) and less prosperous high power distance, collectivist, Asian countries (such as China, India and Singapore). Several existing theoretical frameworks for regional and cultural analysis discuss above may provide more context.

It is noteworthy that cultural dimensions and economic prosperity were found to be closely linked. Most individualist regions with low PD scores tend to be more prosperous and developed (for instance, Nordic and Germanic Europe and Anglo-Saxon region). In contrast, most collectivists countries with high PD scores belonged to Lower or Lower Middle-income regions (such as the South Asian region and Sub-Saharan Africa). The world maps in Figure 2.6 and Figure 2.10 illustrate this geo-cultural and socioeconomic overlapping in detail.

Even though a large number of courses have been predominantly conceptualized and developed by so-called low-context, individualist cultures (the USA, few European countries such as Scandinavian cluster), the need for overall diversity and that specific requirement embraced by high-context, collectivist countries should not be disregarded (Jadin & Gaisch, 2014). This, in fact,
leaves a door open for further research into diverse MOOC development and production. While previous studies have indicated that regional belonging and other cultural constructs significantly impact MOOC learning behaviour. No research looked at the geo-culture concerning learners’ engagement with various elements of learning designs. As such, this research project aims to fill this gap in knowledge by probing the learning engagement in the context of learners’ geo-cultural and socioeconomic groups.15

**RQ 2.3** How and to what extent does engagement with different learning design elements differ between the geo-cultural contexts?

**RQ 2.4** How and to what extent does engagement with different learning design elements differ between the socioeconomic contexts?

The research further quantifies the extent of mediation contexts perform in the link between learning design and learners’ persistence (building upon RQ 3.1).

**RQ 3.2** How and to what extent does the association between learning design elements and learner persistence (from RQ3.1) differs between geo-cultural contexts?

**RQ 3.3** How and to what extent does the association between learning design elements and learner persistence (from RQ 3.1) differ between socioeconomic contexts?

### 2.6 GEO-CULTURAL CONTEXTS AND LEARNERS’ PERSPECTIVES OF LEARNING DESIGNS

As discussed earlier, behavioural scientists traditionally defined ‘culture’ as ‘collective complexes of learned behaviours and perceptions of individuals in a society’ (Tylor, 1871). Regardless of the extensiveness in clickstream/log-based behavioural data, one critical piece of information remained largely missing, which is what are the learners’ perspectives or their self-reported experiences. However, a search of the literature revealed several potential contextual differences in learning behavioural preferences, as discussed below.

In a related and relevant area of research, studies on the user interface (UI) design and user experience (UX) have explored users’ behavioural intention to use technology, software, website, or other web-based resources. The technology acceptance model (TAM) by Davis (1989) has been widely employed to understand the underlying psychological and experiential factors that potentially influence behavioural intention. The TAM focuses on two primary constructs; perceived usefulness and perceived ease of use, that impact a users’ behavioural intention to use a technology, software, or website. The model was further extended by adding perceived enjoyment as a critical

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15 Also mentioned in Chapter 1, the whole number part in RQs refers to the study number and the fractional part represents the actual question number. RQ 2.3 therefore implies third research question in Study 2.
experiential aspect that affects behavioural intention as well as perceived usefulness and ease of use (Hornbæk & Hertzum, 2017; Davis et al., 1992).

Furthermore, usefulness and enjoyment have consistently been hypothesised in the literature as the main determinants of continuing usage of technology or web-based multimedia resources. Thus, perceived usefulness pertains to a user’s belief that target behaviour (i.e., learning resource use) or object (i.e., learning resource) will enhance their performance and/or add to their knowledge (Davis, 1989). At the same time, perceived enjoyment refers to the degree to which a user finds the target behaviour (i.e., learning resource use) or object (i.e., learning resource) enjoyable, regardless of the consequences for their performance (Davis et al., 1992). Several studies found perceived enjoyment to positively correlate with users’ self-reported current use and self-predicted future use (see, for example, Teo & Noyes, 2011; Teo et al., 1999). However, others found the effect of perceived enjoyment on (positive) attitude (towards, and thereof intention to use the technology/resource) to be stronger than that of perceived usefulness and perceived ease of use (Hornbæk & Hertzum, 2017). Figure 2.11 illustrates these links.

![Diagram](image)

Figure 2.11 The causal relationship between perceived enjoyment and other constructs from TAM. (Source: (Sun & Zhang, 2006))

A distinct research direction has recently emerged within UI design and UX that amalgamated cross-cultural frameworks with TAM constructs and emphasised the importance of *culturally adaptive interface designs*. The term *culturally adaptive here* refers to designing software, websites and other web-based resources that adapt their *content type (text versus visuals, for example)* and look
and feel (like colours, interface design, modalities) to suit the visual preferences of users from dissimilar geo-cultural contexts (Reinecke & Bernstein, 2013, 2011). These interesting pieces of research proposed a unique personalised approach to cultural adaptivity, whereby the potential influences of culture for each user are acquired and then stored in a personal user model instance. The model instance used adaptation rules derived from related literature, and mapped onto user interface adaptations. The derived rules, for example, included different access and navigation possibilities, and friendly error messages for users with low PD scores and comparatively fewer links, linear and minimized navigation possibilities and strict error messages for users with high PD scores.

Overall, the findings from culturally adaptive interface designs studies revealed that identifying with particular cultural groups may influence individuals’ aesthetic and visual preferences. It was further found in the relevant work that the countries with proximity within a region seem to share similar choices (see Reinecke & Gajos, 2014). For example, users from Nordic and Germanic Europe (countries such as Finland, Germany) preferred an interface design with low visual complexity along with low colourfulness, standing in contrast with the users from the Eastern European region (e.g., Romania) or Confucian Asian region (e.g., China) who preferred less complex, but more colourful interfaces. Although interface complexity and colourfulness both can be used to potentially predict differences in visual appeal, complexity was found to be more important as a predictor of appeal than colourfulness (Reinecke & Gajos, 2014).

Even more, interestingly, factors such as a regular exchange of (cultural) values (e.g., due to migration) also affected users’ preferences. Earlier work on culturally adaptive design pointed out that a user’s perceived usefulness (thereof, their satisfaction and enjoyment) concerning a web-based or software interface was closely linked with an underlying sense of accomplishment (Reinecke & Bernstein, 2011, p. 2). Overall, the resulting satisfaction and perceived enjoyment were strongly correlated with (self-reported) current usage and (self-predicted) future usage of the respective web-based resource or software.

2.6.1 Learning Behavioural Preferences in Geo-Cultural Contexts

Among the cultural frameworks discussed in section 2.5.1, Hofstede’s (1994; 2004) analysis was predominantly focused on professional management settings. Furthermore, it was largely replicated and applied worldwide in the academic domain, including teaching and learning. It was even argued that cultural belonging has a potential ability to shape various learning styles (Hofstede, 1994; Hofstede & McCrae, 2004). Recent work in learning sciences has found significant disparities in online education attainment. Several regional, racial, cultural, and socioeconomic factors have been found to influence course engagement and completion rates. Specifically, the factors include learners’ race and ethnicity (Stich & Reeves, 2017; Wladis et al., 2015), geographic
location (Reich & Ruipérez-Valiente, 2019; Kizilcec & Halawa, 2015), nature and extent of social
ingression and help-seeking behaviour (Cagiltay et al., 2020; Ogan et al., 2015), and learners native
language (Guo, 2018; Uchidiuno et al., 2018). Driven by previous extensive research on MOOC
learning environment, the section below draws together four relevant expected behavioural
patterns as well as the role of language of instruction.

a. *Predetermined Learning Path*

According to Hofstede and colleagues (2004), low PD societies tend to stimulate *independent
exploration* more than high PD societies, as the latter stress more on a hierarchical structure. For
content presentation in web-based resources, the relevant design aspect is referred to as
multimodalities (that is, various navigation possibilities) (Reinecke & Gajos, 2014; Reinecke &
Bernstein, 2013). In the context of learning design, we can translate navigation possibilities as
predetermined learning paths or a set sequence of activities in a course. Previous work suggests
that teachers may expect students to find their own paths in a course in societies with low PD
scores. In contrast, in societies with high PD scores, students expect the teacher to outline paths to
follow, and dutifully obey the instructions they receive (Reinecke & Gajos, 2014; Reinecke &
Bernstein, 2013; Hofstede & McCrae, 2004; Hofstede, 1986). This finding may imply that learners
from high PD regions (such as Sub-Saharan Africa, Confucian Asia, Eastern Europe, Latin America,
Latin Europe, Middle East, and Southern Asia) tend to navigate linearly with a preference for a
structured path. In contrast, learners from low PD regions (such as Anglo-Saxon, Germanic and
Nordic Europe) prefer multimodal designs. They are expected to find their own path through
learning activities, following an unstructured, non-linear navigation pattern.

b. *Discussion-based learning activities*

Differences between high and low PD societies have been instrumental in explaining variation in
help-seeking behaviours, and the social relationships individuals develop in online courses. Drawing
on the extensive literature on cultural differences in online learners’ interaction, two distinct
priorities for communication can be identified (Bozkurt & Aydın, 2018; Manathunga et al., 2017; Liu
et al., 2016; Ogan et al., 2015). One is a student-centric approach that appreciates learners’
spontaneous participation in discussion with the minimal agency of the instructor. Two, where the
communication activity is initiated and guided by the instructor or a moderator.

Therefore, when this distinction was operationalized in this research (in Study 4) discussion-based
learning activities were divided into two types: instructor-led discussion (i.e., course steps in
FutureLearn titled as *discussion*) and user-led discussion (i.e., use of FutureLearn MOOCs’
functionality that allows learners to comment or start a discussion underneath any course
activities). Previous work suggests that virtually all communication activities are expected to be
initiated by the teacher in societies with high PD scores, where learners would only speak when invited by the teacher (Hofstede, 1986). In contrast, in societies with low PD scores, the learner initiates any communication as they tend to speak up simultaneously, regardless of the discussion group size (Hofstede, 1986).

c. Reading material (articles) versus videos

As discussed earlier, while exploring the diversity in MOOC production and content development, Bayeck & Choi (2018) found that culture influences learners’ understanding and interpretation of images and other audio-visual or textual content. Together with the culturally adaptive user interface designs, several researchers recently examined the relationship between culture or region and users’ interaction with different types of course content (Uchidiuno et al., 2018; Z. Liu et al., 2016). They investigated different preferences among learners for image-to-text ratios. In line with other investigations (Uchidiuno et al., 2018; Reinecke & Gajos, 2014; Reinecke & Bernstein, 2013), this research used a similar approach in learning design and formulated two distinct preferences. The first is an appreciation for learning from text (article, video transcripts, etc.), and the second is a preference for visual or video-based learning material. Related work points out that learners from societies with high individualism scores (such as Latin Europe, Nordic Europe, Anglo-Saxon, and Germanic Europe) may prefer to learn from text-based learning content. At the same time, learners from collectivist societies (such as Eastern Europe, Latin America, Sub-Saharan Africa, Middle East, Southern Asia, and Confucian Asia) may show a relatively strong preference for visuals or video-based content in a course (high image/visuals-to-text ratio).

d. Assessment activities

Finally, the review of relevant work identified a slightly challenging and perhaps the most controversial learning preference that has been reported in the literature. Previous work (Cagiltay et al., 2020; Hone & El Said, 2016) evidenced learners’ inclination to gain a certificate, with or without gaining knowledge. This research further examines the contextual differences in the preference for competence over certification (or vice versa). According to Hofstede (1986), collectivists may prefer acquiring a certificate over competence. Originally phrased in the cross-cultural literature as “in collectivists societies, education is a way of gaining prestige in one’s social environment and of joining a higher status group (“a ticket to a ride”). Where Diploma or certificates are important and displayed on walls and acquiring certificates even through illegal means (cheating or corruption) is more important than acquiring competence.” (Hofstede, 1986, p. 12). The same literature presents the exact opposite expected behaviour from individualist societies, i.e., a strong preference for competence over certification.
Therefore, two potential extremes can be formulated in learning behaviours expected from different geo-cultural regions (Study 4 discussed in Chapter 4 elaborates how these extremes were operationalized in this research). However, at the start of the research, it was anticipated that participants’ self-reported behavioural preferences would lie somewhere between these two extremes.

**Language of instruction and learners’ perspectives**

As MOOCs started in the US, most MOOCs to date use English as the primary language of instruction. In addition to broader cultural and regional factors influencing learners’ participation, language is also closely linked with learners’ engagement. Several studies found that online learners with a non-native English speaking background may face additional language-related challenges due to difficult or unfamiliar words, linguistic complexities, or accents (Rets & Rogaten, 2020; Uchidiuno et al., 2018, 2016). It was also found that for these learners, content comprehension occasionally needs further audio-visual support and more time with the learning resource (Nguyen et al., 2020; Uchidiuno et al., 2018). Interestingly, even within highly technical courses such as computer programming, non-native English-speaking learners have reported a desire for instructional material in simplified English, with fewer cultural-specific jargon and more visuals and multimedia support (Guo, 2018).

Against this background, Study 4 in this thesis examined how learners perceive the role of learning designs towards their engagement in a course. In doing so, Study 4 explored learners’ self-reported perspectives and their behavioural preferences in the MOOC learning environment. In this regard, Study 4 aims to answer the following specific research questions:

**RQ 4.1** What are learners’ perceptions of various learning design elements (i.e., activity types, predetermined path) in relation to their engagement in the course?

**RQ 4.2** In what ways do learners’ perceptions (from RQ 4.1) differ between geo-cultural contexts?

As discussed in detail in Chapter 3, the mixed-method approach, which was used to answer these final two questions, elaborated on the empirical findings from the first three studies.

**2.7 CONCLUSION**

In conclusion, this PhD research aimed to address the gaps in the reviewed literature on the contextual differences in learners’ engagement in MOOC learning designs. This thesis aims to fill these gaps using the findings from four large, interlinked studies designed to address the emerged research questions. This chapter has provided a summary of current research, highlighted the existing gaps in knowledge, and finally presented the research questions to address these gaps. The following chapters in this thesis describe how this PhD research offers evidence-based, actionable
insights that MOOC instructors and learning designers can use to make MOOCs learning spaces more inclusive and diverse. The next chapter in this thesis provides details of the overarching methodologies employed in this research while seeking answers to the research questions listed above.
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Chapter 3 Methodology

3.1 INTRODUCTION
As stated in previous chapters, this thesis consists of four interlinked studies presented in Chapters 4 through 7. Chapter 2 provided a review of recent literature and highlighted several knowledge gaps leading to the research problems addressed in this thesis. Chapter 3 offers an overarching view of theoretical frameworks, methodologies, and the rationales behind each method adopted across all four studies. The chapter starts with a description of the main philosophical underpinnings of this research (section 3.2). Next, section 3.3 presents an overview of the research design, introducing the study design, context, and instruments. The subsequent section (3.4) discusses in detail the various research methods used for data analysis. Finally, section 3.5 addresses ethical considerations and privacy concerns.

3.2 THEORETICAL PERSPECTIVES AND PHILOSOPHICAL UNDERPINNINGS

3.2.1 Research Philosophy
The central motivation behind this research was to understand how learners’ contexts are potentially linked with learning processes and engagement in various MOOC learning designs. Since the work was interdisciplinary in nature and involved several diverse research fields (i.e., educational science, design science, cross-cultural research), it was imperative to first look for the key philosophical principles that eventually formulated the four research designs. The philosophical underpinning of a research design helps devise the study contexts and informs the selection of appropriate methods. Therefore, it is essential to examine various research paradigms before opting for the one aligned with the overall research goals.

In social sciences, research paradigms are referred to as conceptual and practical research tools used to solve a specific research problem (Kaushik & Walsh, 2019). While several philosophical paradigms may guide the structure and organisation of a research problem, they primarily share three common elements: Ontology, Epistemology, and Methodology (Twining et al., 2017). Ontology offers various assumptions about the nature of reality (answering the questions like What is reality?) (Kaushik & Walsh, 2019). Epistemology refers to the assumptions about how one gains knowledge and elaborates the nature of the relationship between the knower and known (concerning: How do we know what reality is?) (Kaushik & Walsh, 2019). Methodology is rather a broad term, concerned with the shared understanding of an appropriate means for gaining knowledge, and an overall shared understanding of research language. The choice of methodology can only be evaluated based on the original research question and the overall goals and purposes of the research project (Twining et al., 2017; Morgan, 2007).
Specific research paradigms (i.e., conceptual and practical research tools) guide researchers in their decision-making process. In educational sciences, researchers often follow one of the three popular research paradigms: positivism, interpretivism, and critical realism (see Table 3.1 for more detail) (Kaushik & Walsh, 2019; Twining et al., 2017). Nevertheless, a research paradigm only represents a conceptual framework and should not be viewed as a static and unchangeable entity. It should be viewed as an approach to formulating a research problem and then finding ways (methods) to address it. Perhaps for these reasons, a fourth paradigm, known as the pragmatic paradigm, is getting increasingly common. This research paradigm encompasses empirical and mixed-method research and conveniently combines various elements from positivism, interpretivism, and critical realism paradigms. Table 3.1 provides a comparative summary of these four research paradigms, including their underlying ontology, epistemology, and methodology. The table separately lists related methods used for data collection and analysis.

3.2.2 Pragmatic Approach

The research questions addressed in this thesis are complex in many ways. The problems associated with the exploration of clickstream data from online learning platforms like MOOCs needed to adopt a quantitative approach. One solution is to assume that there is one single reality that is measurable with reliable tools and can be analysed using various appropriate quantitative methods; that is, a positivist approach. But other constructs such as cultural identities and affiliated social, socioeconomic, and behavioural experiences are generally considered to be subjective and hard to be represented by one single truth. That approach should be either interpretive or critical, depending upon which lens the researcher prefers to employ. As outlined in Table 3.1, both of these approaches are typically associated with qualitative methods and rely as much as possible on the research participants' views to develop subjective meanings of the relevant phenomena (Kaushik & Walsh, 2019; Twining et al., 2017).

Suppose learners' behavioural traces are examined in isolation from their demographics and their experiences with the learning designs. In that case, the findings may potentially be limited and provide only a partial understanding of contextual differences in learners' experiences within various learning designs. At the same time, a subjective explanation of learners' (self-reported) learning design experiences alone may not provide an in-depth and generalisable understanding of the (otherwise) observable behavioural differences, particularly between dissimilar contexts. Both approaches seemed inadequate if used individually, as they may lead to inconsistent findings (i.e., telling incomplete stories). Therefore, addressing the questions in this research called for the flexibility a pragmatic research paradigm offers.
Table 3.1 A comparison of research paradigms common in Educational research. [Source: (Kaushik & Walsh, 2019; Twining et al., 2017; Bryman, 2016)]

<table>
<thead>
<tr>
<th>Paradigm</th>
<th>Ontology</th>
<th>Epistemology</th>
<th>Methodology: Data Analysis Methods</th>
<th>Methodology: Data Collection Methods</th>
</tr>
</thead>
<tbody>
<tr>
<td>Positivism</td>
<td>There is one single truth waiting to be found. There is one single reality.</td>
<td>Reality is measurable and can be explained with valid, reliable tools.</td>
<td>Quantitative</td>
<td>Experiment, Survey, Statistical Test</td>
</tr>
<tr>
<td>Interpretive / Constructivism</td>
<td>There is no single reality. There are multiple realities that are socially constructed. The researcher works as an attached internal observer.</td>
<td>Reality must be interpreted (or created) through the lens of observed group members.</td>
<td>Qualitative</td>
<td>Interviews, Observation, Case study, Narrative</td>
</tr>
<tr>
<td>Critical realism</td>
<td>Reality is stratified and socially constructed. Realities are shaped by social, political, cultural, economic, ethnic and gender-based forces.</td>
<td>Reality is discovered through the facts, events, and the lens of the perceived experience of the observed group members.</td>
<td>Qualitative</td>
<td>Interview, Observation, Focus group, Design-based research</td>
</tr>
<tr>
<td>Pragmatism</td>
<td>Reality is the practical effects of ideas. Therefore, there can be single or multiple realities that are open to empirical enquiry.</td>
<td>Reality exists independent of the researcher and can be discovered by the best-suited method for each problem.</td>
<td>Quantitative and qualitative (mixed methods)</td>
<td>A combination of any of the above</td>
</tr>
</tbody>
</table>
As a research paradigm, pragmatism allows for multifaceted, multi-layered explanations of complex realities, an approach sometimes referred to as the *freewheeling orientation of newer approaches* (Kaushik & Walsh, 2019, p. 2). In this research, a flexible, mixed-method approach was needed to understand learners' behaviours and experiences, whereby the focus was on the consequences of research and the *research questions* rather than on the methods (Kaushik & Walsh, 2019; Morgan, 2007). The pragmatic research paradigm is often associated with mixed methods or multiple methods. If pragmatically used, mixed methods may lead to an understanding that can be both objective and subjective, conveniently supporting each other. Also, the pragmatic approach focuses on the practicalities to address the research question while *'brushing aside the quantitative/qualitative divide'* (Feilzer, 2010).

Like other research paradigms, there are several methodological limitations attached to pragmatism. Although pragmatism embraces the two divergent perspectives, one is supported strongly by positivists who emphasize acquiring knowledge through empirical methods and hypothesis testing, and the other is backed by constructivists who typically assert qualitative approaches. Pragmatism offers a researcher the flexibility and independence to select the methodology appropriate to address the respective research question. But the independence that allows these methodological choices, offers several challenges; for example, difficulty in acquiring skills to implement multiple methods, unnecessarily influence of researchers’ personal history and life experiences, their belief systems and socio-political position (Kaushik & Walsh, 2019). Some criticise pragmatism for being an approach *too contextual and problem-centric* (Kaushik & Walsh, 2019, p. 6). Nonetheless, these aspects and the flexibility the pragmatism offers were few of the reasons this approach was more appropriate. On a personal note, as discussed in detail in several subsequent sections in this chapter and the following chapters, I did not incline to *'be the prisoner of a particular [research] method or technique'* (Feilzer, 2010, p. 3). Therefore, the pragmatic research paradigm was chosen as the theoretical foundation for this research.

3.3 RESEARCH DESIGN

3.3.1 Background and Context

This research set out to study how online learning designs can be adapted at scale in various contexts to improve online learners’ persistence and engagement. As discussed in Chapter 2, this thesis aimed to address eleven research questions in four interlinking studies as follows:

**Study 1: Role of learners’ contexts in online learning.**

Study 1 provided a meso-level understanding of the association between learners' demographic characteristics and their success in formal online learning. Notwithstanding in the online learning domain rather than MOOCs in Studies 2-4, Study 1 provided a firm foundation for this research.
project. The study started before formal ethical approvals were received to use FutureLearn data in this PhD project. Therefore, it utilised publicly available datasets from the *OU Analyse* project (see Kuzilek et al., 2017, 2015).\textsuperscript{16}

Study 1 examined the predictive association between learners’ demographic characteristics (regional context, socioeconomic context, education level, age, gender, and disability status) and their success in online courses (whether in the respective module they failed, passed, or passed with distinction). This study aimed to address the following research questions.

**RQ 1.1** To what extent is there an association between learners’ demographic characteristics (i.e., Regional context, Socioeconomic context, Education, Age, Gender, and Disability) and online learning outcomes throughout the online course?

**RQ 1.2** To what extent does the association (from RQ 1.1) vary across different online courses with distinct learning designs?

**Study 2: Engagement with learning design elements and contextual differences.**

Study 2 explored variations in learning processes and activity engagement behaviour in a diverse FutureLearn MOOC. Before the analysis, the study categorized learners into three groups based on their clicking behaviour (Markers, Partial Markers and Non-Markers, the approach has been discussed in detail in Chapter 5). Furthermore, the study observed how learning activity engagement behaviour varied between ten geo-cultural and four socioeconomic contexts.

**RQ 2.1** How and to what extent does engagement with different learning design elements (i.e., (a) assimilative learning activities (e.g., articles, videos), (b) communication activities (e.g., discussions), and (c) assessment activities (e.g., quizzes)) differ between learners?

**RQ 2.2** How and to what extent do temporal learning paths (i.e., sequences of learning activities) differ between learners?

**RQ 2.3** How and to what extent does engagement with different learning design elements differ between the geo-cultural contexts?

**RQ 2.4** How and to what extent does engagement with different learning design elements differ between the socioeconomic contexts?

\textsuperscript{16} Study 1 was further replicated using data from ten large FutureLearn MOOCs, and the results were found to be comparable. See Appendix B for more detail.
**Study 3: Predictive link between learning design elements and persistence; Contextual differences.**

While Study 2 pointed dissimilar activity engagement behaviour (see Chapter 5), in general and across the contexts, it was still unknown if the number of learning design elements could be potentially linked with how far a learner progresses in a course. Thus, using a large, diverse sample, the subsequent Study (Study 3) sought the relationship between various learning design elements (i.e., articles, videos, discussions, and quizzes) in a course and learners’ persistence. This study also examined the extent to which the predictive association between learning design factors and persistence varies between ten geo-cultural and four socioeconomic contexts. It is worth highlighting that large early dropout from MOOC courses was the reason for selecting persistence over other summative success measures (such as certification or completion). Overall, this study sought to address the following research questions.

**RQ 3.1** How and to what extent does the number of learning design elements (i.e., (a) assimilative learning activities (e.g., articles, videos), (b) communication activities (e.g., discussions), and (c) assessment activities (e.g., quizzes)) in a course predict learners' persistence?

**RQ 3.2** How and to what extent does the association between learning design elements and learner persistence (from RQ 3.1) differ between geo-cultural contexts?

**RQ 3.3** How and to what extent does the association between learning design and learner persistence (from RQ 3.1) differ between socioeconomic contexts?

**Study 4: Learners’ perception of various learning design elements; Contextual differences.**

Although Study 3 provided an in-depth understanding of learners' persistence as a function of learning design and learners' regional and socioeconomic contexts, it still utilised trace data or in-situ data from MOOC logs. In fact, none of the first three studies considered learners perspectives. Therefore, Study 4 was conducted to understand how learners perceive the role of learning design towards upholding their engagement in a MOOC. Study 4 further examined the similarities and contrasts in learners' perceptions across various geo-cultural contexts.

**RQ 4.1** What are learners' perceptions of various learning design elements (i.e., activity types, predetermined path) in relation to their engagement in the course?

**RQ 4.2** In what ways do learners' perceptions (from RQ 4.1) differ between geo-cultural contexts?

It is essential to highlight here that all studies, were conducted in the context of the MOOC learning environment, except for Study 1, which used data retrieved from the OU online courses.
Altogether, the four listed studies filled the critical gap in understanding learners’ persistence in online learning design in various contexts. Figure 3.1 provides a conceptual link between the four studies discussed in this thesis, while Table 3.2 gives a brief overview of the overall study design.

![Figure 3.1 Conceptual link between four studies in this thesis.](image-url)
The studies in this thesis have employed a wide range of quantitative and qualitative methods. The following sections in this chapter explain the description and motivation for key methods used in each of the studies.

### 3.3.2 Data Selection and Pre-processing

This part gives a brief overview of the data sets and pre-processing used in each of the four studies. The section further describes the various theoretical strands for regional/geo-cultural and socioeconomic categorisation and then rationalises the specific categorisation chosen in this research.

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**Table 3.2 An overview of study design**

<table>
<thead>
<tr>
<th>Study</th>
<th>RQ</th>
<th>Sample</th>
<th>Instruments</th>
<th>Methods</th>
</tr>
</thead>
<tbody>
<tr>
<td>Study 1</td>
<td>RQ 1.1, RQ 1.2</td>
<td>n = 8581, across four OU modules (courses)</td>
<td>Data from OU Analyse project. Registration data, Assessment outcomes.</td>
<td>Decision tree based predictive modelling (see section 3.4.1)</td>
</tr>
<tr>
<td>Study 2</td>
<td>RQ 2.1, RQ 2.2, RQ 2.3, RQ 2.4</td>
<td>n = 2,086, from one FutureLearn MOOC</td>
<td>Learner location data, Step activity data</td>
<td>Descriptive statistics, Process mining (see section 2.4.2 and section 3.4.1), Kruskal Wallis and follow-up pairwise comparisons (see section 3.4.1)</td>
</tr>
<tr>
<td>Study 3</td>
<td>RQ 3.1, RQ 3.2, RQ 3.3</td>
<td>n = 49,582, across twelve FutureLearn MOOCs</td>
<td>Learner location data, Step activity data</td>
<td>Survival analysis (see section 3.4.1), Interaction analysis within survival (see section 3.4.1), LASSO, Cross validated feature selection (see section 3.4.1)</td>
</tr>
<tr>
<td>Study 4</td>
<td>RQ 4.1, RQ 4.2</td>
<td>n = 22, FutureLearn learners from seven geo-cultural regions</td>
<td>Semi-structured interview questions, Artifact (Visualization)</td>
<td>Thematic analysis (see section 3.4.2), Sentiment mining (see section 3.4.2), Descriptive statistics</td>
</tr>
</tbody>
</table>
**Study 1**

As discussed earlier, Study 1, in this thesis, used data from Open University Learning Analytics Datasets (OULAD) OU Analyse project (Kuzilek et al., 2017, 2015). The dataset contains learners' demographic information together with their assessment results. The dataset\(^\text{17}\) also contains aggregated clickstream data of learners' interaction with the OU's Virtual Learning Environment (VLE). The data is freely accessible\(^\text{18}\) under a *CC-BY 4.0* license (Kuzilek et al., 2017). The courses listed in OULAD fulfilled specific criteria. For example, the courses were large (number of enrolment > 500), data were available from at least two offerings, VLE/clickstream data was obtainable. Finally, for the analytical purpose, there was a significant number of unsuccessful (failed) learners. Study 1 used a sufficiently large subset of OULAD. The overall sample comprises 8,581 UK-based learners enrolled in four diverse courses (modules) offered between 2013 and 2014.

In terms of the regional grouping, the United Kingdom of Great Britain and Northern Ireland has been subdivided into 13 regions. While taking the course, learners in Study 1 were geographically located in one of the following thirteen regions: East Anglian Region, East Midlands Region, Ireland, London Region, North Region, North Western Region, Scotland, South East Region, South Region, South West Region, Wales, West Midlands Region, and Yorkshire Region.

Moreover, the OULAD used the Index of Multiple Deprivation (IMD) to identify learners who belonged to deprived areas. The index originated from a UK government qualitative study of regions across the country that produced a ranking system to determine the relative deprivation status (Smith et al., 2015). Overall, IMD identifies relative levels of social and economic deprivation of the neighbourhood based on seven distinct dimensions; income deprivation, employment deprivation, health deprivation and disability, education skills and training, barriers to housing and services, crime rate, and living environment. The data selection and detailed pre-processing for Study 1 have been discussed further in Chapter 4.

**Study 2 through Study 3**

After receiving ethical approvals for this project (see section 3.5 in this chapter) and acquiring access to FutureLearn MOOC platform data, subsequent studies (Study 2 through Study 3) used FutureLearn datasets containing information about learners enrolled from all around the world. This research used IP-based locations in line with the extensive previous research (Reich & Ruipérez-Valiente, 2019; Kizilcec et al., 2017). As discussed in section 2.5.1, GLOBE (Global Leadership and Organizational Behaviour Effectiveness) theoretical framework was used for

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\(^{18}\) [https://analyse.kmi.open.ac.uk/open_dataset](https://analyse.kmi.open.ac.uk/open_dataset)
learners' geo-cultural categorisation (House et al., 2004). As for socioeconomic contexts, the World Bank classification of world economies was used to aggregate learners' countries into global socioeconomic groups (see section 2.5.2). This chapter further proceeds by laying out the several dimensions of both classification schemes used in Study 2 through Study 3. Note that the same geo-cultural classification scheme was used in Study 4 as well.

**Geographical and Cultural (Geo-cultural) Categorisation**

Considering the differences and extent of coverage of different cultural frameworks discussed in Section 2.5.1, GLOBE societal clusters' extension seemed the most appropriate framework for this research. Firstly, with thousands of researcher-years invested in the study, GLOBE has introduced a fine-grain look into cross-cultural research, which was sparsely available in other frameworks. Also, the Extended-GLOBE study introduced a few more essential culture-focused items, such as language and colonial heritage. The empirical method also accommodated intuition and familiarity in its cultural categorisation (in the form of geographic proximity and ethnic distribution, for example). Secondly, it is theory-driven and deeply rooted in the large body of cross-cultural research. Thirdly, this framework originated the investigation of multiple industries and further continued to add additional generalizability, encompassing a large number of nation-cultures or countries from all over the globe. Lastly, previously ignored (category: Uncategorised) countries were included in the design, enabling more accurate categorisation. Thus, using the Extended-GLOBE framework will allow a better understanding of geo-culture and its effect on learning in MOOCs as MOOC learners are geo-distributed or geographically distributed with planetary footprints, where learners reside in all continents and originate from numerous countries.

Using this framework in Study 2 through Study 4, learners were grouped into the ten geo-cultural groups listed above. The framework characterises a comprehensive view of global regions and cultural constructs in those regions. See section 2.5 in Chapter 2 for a discussion on how this thesis mainly draws upon two cultural dimensions; (i) Power Distance (PD) Index and (ii) Individualism/Collectivism, and how the ten geo-cultural groups were divided into simplistic subgroups: one with high Power Distance and the other with low Power Distance, similarly one subgroup with high collectivism score and other more individualist.

**Socioeconomic Categorisation**

As discussed earlier in section 2.5.2, a variety of methods can be adopted to assess poverty levels. Each has its advantages and drawbacks. Several MOOC studies used HDI scores as a proxy for learners’ socioeconomic contexts (see for example, Reich & Ruipérez-Valiente, 2019; Kizilcec, Saltarelli, et al., 2017). Still the measures associated with HDI are often criticised in the literature for a lack of consideration of technological development in the respective country, as well as the
measurement errors from underlying statistical methods, which can lead to country misclassification (Wolff et al., 2011). Nevertheless, GNI per capita may not directly represent the level of development of welfare for the respective country. But again, there may be some caveats attached to this classification scheme as well. For example, this measure may not consider informal, subsistence activities or inequalities in income distribution in the respective country. This limitation may be more imperative in Low-income societies with potentially large wealth gaps.

Previous research has reported many reasons why GNI per capita could be more fitting for country classification intended for analytical purposes. One main reason is linked to availability and reliability. GNI per capita is an easily accessible measure of multiple deprivations, where the indicator is found to be connected with other well-being measures (Fantom & Serajuddin, 2016). For example, GNI per capita reasonably correlates with other accepted indicators of development outcomes such as secondary school enrolment, health-related indicators and poverty headcount ratio (Fantom & Serajuddin, 2016). Moreover, the World Bank classification of economies based on GNI per capita covers virtually all countries and is updated annually (Fantom & Serajuddin, 2016). Therefore, it seemed the most suitable approach to employ the World Bank income level categorisation to identify learners’ socioeconomic contexts in Study 2 and Study 3.

3.4 RESEARCH METHODS

3.4.1 Explainable Learning Analytics and Educational Data Mining

There are growing concerns around explainability (or lack of it) in the field of Learning Analytics (LA) and Educational Data Mining (EDM). While many learning analytics methods and products are meant to support (human) decision-making, the lack of comprehension in the 'black-box' algorithms often suggests the opposite (Rudin & Radin, 2019). These otherwise efficient and accurate models can create an environment of mistrust, and potentially restrain instructors’ (or learning designers’) control over strategies to support students at risk, a peril recently raised by Selwyn, (2019) as diminishing the ability of students and teachers to exercise judgment and expertise in the overall (learning) process. To date, many EDM methods used to understand the MOOC learning environment work as black boxes (Slater et al., 2017; Baker & Inventado, 2014; Papamitsiou & Economides, 2014). This research project aimed to 'understand' the role of learning design in different contexts. Thus, most empirical approaches employed in this thesis can roughly fall into the category of explainable learning analytics (XLA). Note that the term is used as an

19 The black box models are created directly from data by a machine learning algorithm. That means that humans, even those who design them, cannot understand how variables are being combined to make predictions. See Rudin & Radin (2019), for several interesting arguments related to accuracy-interpretability tradeoff in machine learning.
analogy to explainable Artificial Intelligence (XAI) in learning science\textsuperscript{20} (Arrieta et al., 2020, p. 2; Gunning, 2017) (see Figure 3.2).

![Figure 3.2 Illustration explaining explainable and interpretable AI methods [Source: (Gunning, 2017)]](image)

In this thesis, the list of methods starts with the decision trees, a predictive modelling technique often used in EDM/LA research (see, for example, Asif et al., 2017; Yehuala, 2015; Oskouei & Askari, 2014; Kabakchieva, 2013) that provides interpretable results (Study 1). In line with Saint et al. (2021), and Davis et al. (2016), Study 2 employed illustrative process mining methods. Finally, when a rather complex statistical method (i.e., survival analysis\textsuperscript{21}) was used, it accompanied appropriate machine learning-inspired methods (Lasso/ Cross validated feature selection) (Study 3 followed the approach recommended by Singer, 2019; and used by Kizilcec et al., 2017; Reich, J., 2014 etc.). Study 3 opted for an intuitive two-fold analysis approach (interaction analysis and subset analysis), which increased reliability and introduced the interpretability of the outcomes. Study 4 employed a mixed-method approach and used thematic analysis, followed by sentiment mining, to understand qualitative data collected in Study 4 (resembling an approach presented in Mittelmeier et al. (2018)). Next, this section describes specific methods employed in each of the four studies and compares them with other potentially useful alternatives and a rationale for method selection.

**Study 1: Decision Trees for explanatory modelling**

The empirical approach adopted for Study 1 was based on Decision Trees (DT), a simple, yet powerful, multivariate, non-parametric supervised learning method used for nominal classification. DT assumes an elaborative approach to understanding the relationships between independent and dependent variables. Without altering or modifying the data, the resulting model produces human-

\textsuperscript{20} Drawing insights from psychology and other social sciences, explainable AI or XAI refers to creating a suite of AI techniques that (1) produce more explainable models while maintaining a high level of learning performance (e.g., prediction accuracy), and (2) enable humans to understand, appropriately trust, and effectively manage the emerging generation of artificially intelligent partners.

\textsuperscript{21} Described as ‘truly longitudinal method’ by Singer (2019) in their recent work on quantitative educational research, an interesting read arguing in favour of analytic methods such as survival analysis.
readable rules that explain the knowledge the model learnt from the data. In terms of algorithmic transparency, the DT based models provide a direct understanding of the prediction process (Arrieta et al., 2020).

These algorithms produce results in a graphical or hierarchical structure, accompanied by the rule expressions to support decision making. The tree induction is a recursive top-down process. In other words, it does not require any prior assumptions regarding the type of probability distributions satisfied by the class and predictive variables (Han et al., 2011; Tan & Steinbach, 2006). However, one caveat is that DT may occasionally suffer from poor generalisability of models, mainly because no post-hoc analyses are involved. Various Tree ensembles offer the potential to overcome this issue, for example, by aggregating the tree performance using different subsets of training data. The outcome can assist in understanding variable importance, but the outcome largely loses the useful properties of transparency and ease in interpretability.

Theoretically speaking, the DTs in Study 1 can be considered a compression method for the target demographic characteristics (Han et al., 2011; Mannila, 2000). The method uses a white box model, which means that if a given situation is observable in a model, the conditions are easily interpretable. By contrast, in a deep learning black-box model, such as Artificial Neural Network (ANN), outcomes are usually difficult to interpret. Other similar white box rule-based learning methods can also be used for knowledge representation in expert systems. In fact, the rule-based methods may provide transparent and easily interpretable results comparable to DT results, but they often suffer from low accuracy (Arrieta et al., 2020).

Indeed, there are several other potentially comparable techniques. In terms of algorithmic transparency and interpretability, DT can be equated with at least two other algorithms often used for classification modelling, named K-Nearest Neighbours (KNN) and multinomial logistic regression (multinomial because Study 1 outcome contained three classes, providing sufficient accuracy yet more nuance and more insights than a two-class classification (i.e., pass/fail) as highlighted recently by (Asif et al., 2017)). However, in comparison to these methods and other similar algorithms like Bayesian Models (e.g., Naïve Bayes) and Support Vector Machines (SVMs), the standard DT results are accurate enough, easily interpretable, and intrinsically support nominal and categorical variables, such as those used in Study 1 (Breiman, et al., 1984). Figure 3.3 illustrates the positioning of DT based models in a trade-off between model accuracy and interpretability (Arrieta et al., 2020).
The trees generally converge well on the data size used in Study 1 (Farrelly, 2017). Also, DTs efficiently handle multiclass problems. For these reasons and given the explanatory nature of the research problem in Study 1, this analysis method seemed most appropriate. A range of classical DT algorithms can be found in literature, such as Iterative Dichotomiser3 or ID3 (Quinlan, 1986), Chi-Square Automatic Interaction Detector or CHAID (Kass, 1980), Classification and Regression Trees or CART (Breiman et al., 1984), and C4.5 (Quinlan, 1996). Classification models in Study 1 employed a traditional CART algorithm from R package rpart (Therneau et al., 2010). The method has been discussed further in Chapter 4 of this thesis.

A note of caution is due here. While examining LA and EDM literature, we found various predictive modelling techniques that are currently being used to model learning outcomes and to find meaningful patterns in large volumes of educational data (Gardner et al., 2019; Gašević et al., 2016; Papamitsiou & Economides, 2014; Baker & Inventado, 2014). Only a few selected techniques are discussed here. The section also compares the predictive and interpretive powers of various modelling approaches in detail, which may or may not be linked with the type of input researchers introduce (six demographic characteristics in this case).

**Study 2 (RQ 2.1 - RQ 2.2): Educational Process Mining (EPM) to map learning processes**

Process Mining is a set of emerging techniques to extract process-related knowledge from the events logs. Educational Process Mining (EPM) is an application of Process Mining techniques in the
academic domain (see Bogarín et al. (2018) for a survey on EPM). Among other XLA methods, EPM is yet another powerful illustrative technique often used to draw end-to-end learning processes (Saint et al., 2021, 2018; Bogarín et al., 2018).

To understand learners' progression through learning activities (i.e., processual learning, as discussed in section 2.4.2 in Chapter 2), EDM and LA research has been using several methods. Such methods analyse massive clickstream data extracted from various learning environments. But most of these methods assist in explaining hidden patterns that are typically input/output-centric and not process-centric (Slater et al., 2017). Other advanced empirical methods include but are not limited to, Sequential Pattern Mining or associated Stochastic / Probabilistic predictive methods, such as first-order Markov Models (FOMMs) (Saint et al., 2018, 2021; Davis et al., 2016) or Hidden Markov Models (HMM) (Geigle & Zhai, 2017; Jeong & Biswas, 2008), and illustrative methods, such as Graph Mining or Social Network Analysis (SNA) (Geigle & Zhai, 2017; Robinson et al., 2016; Wen & Rosé, 2014). Sequential Pattern Mining and related methods are relatively more suitable for finding partial and successive (sequence/sub-sequence) sets of learning events (Bogarín et al., 2018). These methods along with SNA techniques, provide an illustrative understanding of learning engagement and are particularly suited to finding local processes, short sequences, and subgraphs of interest (see Bogarín et al., 2018; Saint et al., 2018; Slater et al., 2017). Figure 3.4 provides an overview of these and a few other methods and algorithms broadly linked with Process Mining.

Regardless of their robustness in extracting short sequences or local processes, most of these methods may not be appropriate to understand complete end-to-end learning processes as the results will potentially lack a comprehensive understanding of end-to-end learning paths followed by large subgroups of learners (Bogarín et al., 2018; Bannert, Reimann, & Sonnenberg, 2014). Another disadvantage is that these methods make little or no use of time attributes or duration of activity engagement.
Whereas in Process Mining, the term Variant refers to a simplistic view of the end-to-end sequence of activities, analogous to a learning path followed by a significant number of learners (see Figure 3.5). Learners’ navigation patterns through the course activities may provide a potentially better understanding of learners’ temporal behaviours and choices. Therefore, to examine learners’ engagement duration and their activity progression, Study 2 employed EPM methods.

Figure 3.5. List of 140 types of learning sessions. Variant 8 shows four end-to-end interactions (events), with the time associated (variant 8: A typical, simplistic learning path followed by a subgroup of 8 learners).

Study 2 in this thesis compares learners’ transitions through the various learning activities and learn from them. To understand learners’ resource engagement behaviour and develop their temporal navigational patterns (RQ 2.1 to RQ 2.2), Study 2 used multiple exploratory methods typically associated with EPM. As discussed in detail in Chapter 5, section 5.1, based on their clicking behaviours, Study 2 first divided learners into the following three groups: Markers (M), Partial-Markers (PM) and Non-Markers (NM). Next, the analysis focused on estimating and comparing activity access frequency and temporal learning pathways of dominant subgroups of learners in all three groups (M, PM, and NM). Each of the three groups demonstrated a relatively unique learning process, and all learners from a respective subgroup tended to follow a particular learning pathway in the MOOC. For constructing those pathways (or learning process maps), Discovery (Disco) software was used. The software leverages an extended and improved version of the Fuzzy Miner.
algorithm (Günther & Van Der Aalst, 2007), which creates elaborative, uncomplicated process maps and quickly identifies infrequent subgroups.

Recent work examining various EPM algorithms found that the use of Fuzzy Miner algorithm may offer better insights when used to analyse the data about temporal and sequential relations of learning processes (Saint et al., 2021). However, a closer inspection shows that process maps resulting from the Fuzzy Miner algorithm are comparable to those from the FOMM/pMineR algorithm (Saint et al., 2018), except that instead of the transition probabilities, the resulting arcs report the actual number of transitions. In addition, to improve the statistical soundness of the arguments and to see if the subgroups (that is, variants) from the above listed three groups were actually different, chi-square method was used. It is essential to highlight here that activity engagement duration was only recorded for the group of Markers.

**Study 2 (RQ 2.3 - RQ 2.4): Descriptive statistics, Kruskal-Wallis and post-hoc Wilcoxon rank sum test**

Study 2 further explored the extent of learners’ engagement with various learning design elements and how the engagement differed between geo-cultural and socioeconomic contexts. The presence of a large number of subgroups (ten geo-cultural and four socioeconomic subgroups) ruled out the possibility of using the process mining methods (used to address RQ 2.1 and RQ 2.2 as discussed above). Therefore, descriptive statistics and the Kruskal Wallis test were used to measure contextual differences in activity access behaviour. Kruskal-Wallis is a non-parametric test for samples of three or more groups, where the groups are mutually exclusive and independent. The test followed a post-hoc Wilcoxon rank-sum test, which performed comparisons between ten geo-cultural contexts (for RQ 2.3) and four socioeconomic contexts (for RQ 2.4).

Non-parametric tests were opted as the primary analysis methods for the later part of Study 2 because the engagement measurement (frequency of access) was not normally distributed overall or in any context. In the follow-up analysis, the pairwise Wilcoxon test further examined the significance of differences between various pairs of subgroups. For each of the activity types (article, video, discussion and quiz), the activity engagement differences were first explored in the overall learners’ sample and then separately in all three subgroups of learners (M, PM, and NM) from ten geo-cultural clusters (for RQ 2.3) and four socioeconomic clusters (for RQ 2.4). The package R base was used to conduct the analysis.

**Study 3: Survival Analysis to measure learners’ persistence**

Closely following the methodology employed by Kizilcec et al. (2017), and Reich, J. (2014), to evaluate MOOC learners’ persistence, Study 3 used multiple methods associated with survival analysis to quantify the link between the number of different types of learning activities and learner
persistence (RQ 3.1). The same methods were utilised to understand how the survival experience varied between ten geo-cultural contexts (RQ 3.2) and four socioeconomic contexts (RQ 3.3). In general, the goal of survival analysis is to model data where the outcome is \textit{time until the occurrence of an event of interest}. This explanation can be rendered slightly in the case of Study 3, as the outcome was activities accessed by a learner until the event of their dropout.

As discussed in detail in Chapter 2, thus far, many studies have utilised behavioural log data to 'predict' the dropout (a review of the literature on predictive models in MOOCs can be found in Gardner & Brooks, 2018). However, such behavioural data seemed more fitting to be used in a model trained for intervention (i.e., pre/post-treatment variables). Whilst none of the studies in this thesis involved any active interventions. Recent studies have used traditional predictive models to evaluate dropout in similar work in the MOOC learning environment. In the process, the researchers set various thresholds (temporal like week numbers, progression like 50% activity access etc.)(Gardner & Brooks, 2018). The choice of a similar threshold seemed arbitrary in this case, though, because the longitudinal nature of survival analysis methods allowed to look across the entire dataset. Therefore, Study 3 instead preferred the survival analysis methods with the outcome \textit{activities to dropout} (analogy to time-to-event).

Moreover, the approach of using activity access data or similar behavioural data as a predictor to predict persistence seemed not particularly useful. That is because learners who would access more activities (of any type) may naturally appear more persistent. Hence, fixed factors from learning design (i.e., four learning design elements: number of articles, videos, discussion, and quizzes) and the fixed contexts of learners (their geo-cultural and socioeconomic subgroups) appeared as a better choice for predictor (independent) variables.

Note, however, that in terms of temporal persistence (or activity engagement period), Study 3 used methods different from those used in Study 1 and 2, for two reasons. First, not all ten MOOCs used in Study 3 had the same lengths (varied between 4 weeks and 8 weeks). Second, regardless of the actual duration of the course run, all content was made available at the beginning of the course, making overall engagement time irrelevant in the given context. Consequently, the number of days a learner remained active was not correlated with how much content they accessed in the course. Therefore, temporal persistence seemed less informative in this case, and Study 3 pivoted to the operationalisations of persistence that looked specifically at how far in the course activities a learner progressed.

Survival analysis, sometimes referred to as Time-to-event (TTE) analysis, is a useful statistical tool popular in disciplines such as medical research, engineering, and economics. For instance, this method can evaluate a new drug and its dosage efficacy and assess actuarial losses and reliability and the life of devices under different environmental factors (like temperature or humidity). The
specific objective of Study 3 was to determine whether the factors associated with the MOOCs learning environment (number of articles [A], videos [V], quizzes [Q] and discussions [D]) are associated with learners' persistence.

It is essential to highlight here that there are several ways to encode a course design as well as persistence. Study 3 used the actual number of activities in a course design. One alternative operationalisation may be a proportion of learning activities in a course design. But instead of using the actual number, using the proportion of activities may introduce large multicollinearity in predictors (increasing the proportion of one activity means decreasing the proportion of the other). Finally, unlike summative measure of performance (i.e., certification or course completion), persistence is temporal in nature where learners' dropout (thereof hazard to the survival) occurs as the course progresses. In line with previous studies evaluating persistence across the courses, Study 3 also operationalised persistence as the proportion of activities accessed before dropout (an approach mentioned by Singer, 2019; and used by Kizilcec et al., 2017; Reich, J., 2014 etc.).

In terms of analysis methods, firstly, the Kaplan-Meier (KM) curves were used to observe survival probabilities and median survivals. Secondly, the complementary log-rank tests examined the differences between survivals experiences (Rich et al., 2010). Both methods are non-parametric and have no underlying assumptions about the distribution of data. These two methods generate unbiased, univariate descriptive statistics and address fundamental questions such as what proportion of learners will continue learning in their respective MOOCs after a certain point in the course? Finally, for a more nuanced, multivariate analysis, Cox regression was used.
Table 3.3 A comparison of various survival analysis methods (Wang et al., 2017).

<table>
<thead>
<tr>
<th>Type</th>
<th>Method</th>
<th>Advantage</th>
<th>Disadvantage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Non-parametric</td>
<td>Kaplan-Meier</td>
<td>More efficient when no suitable theoretical distributions are known.</td>
<td>Difficult to interpret; May yield inaccurate estimates.</td>
</tr>
<tr>
<td></td>
<td>Life-Table</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Nelson-Aalen</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Semi-parametric</td>
<td>Cox model</td>
<td>The knowledge of the underlying distribution of survival times is not required.</td>
<td>The distribution of the outcome is unknown; not easy to interpret.</td>
</tr>
<tr>
<td></td>
<td>Regularized Cox</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>CoxBoost</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Time-Dependent Cox</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Parametric</td>
<td>Tobit</td>
<td>Easy to interpret, more efficient and accurate when the survival times follow a particular distribution.</td>
<td>When the distribution assumption is violated, it may be inconsistent and can give sub-optimal results.</td>
</tr>
<tr>
<td></td>
<td>Buckley-James</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Penalised regression</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Accelerated Failure</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Time</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 3.3 and Figure 3.6 show a comprehensive comparison of various survival analysis methods. Study 3 utilized the methods written in bold text (see Table 3.3). As illustrated in Figure 3.6, several survival analysis methods are parametric. However, the main challenges in using one of the parametric methods were that the distribution of survival time (distribution of activities accessed in this case) was unclear overall, and large variations were noticed between various contexts (Wang et al., 2017).

Quite common in KM analysis, the study assumed that the survival probabilities remained the same for the learners regardless of their recruitment time, i.e., whether they started early or late. Survival curves were estimated for each course. A log-rank test compared the survival experiences between groups to understand whether the KM survival curves for different groups are identical or overlapping or if there are significant statistical differences in the survival experiences of the groups. A Life-Table followed the KM curves to see if the difference in survival experience was associated with the number of learning activities the learners' groups were accessing. Intuitively speaking, if the number of different learning activities had a link with the progress of learners. Moreover, to quantify this relationship, the Cox regression methods examined the degree to which the number of different learning activities predicts risk to persistence.
To understand the effect of multiple covariates on persistence or survival experience, Study 3 used Cox regression, often referred to as Cox proportional hazard regression. The method is semi-parametric and is used to estimate variation in the hazard function relative to a baseline (Christensen, 1987). Cox regression first quantified the link between the different number of learning activities and the percentage of course activities accessed by a learner (RQ 3.1). Next, the study sought to see how the nature of this link (from RQ 3.1) differed for different geo-cultural subgroups (RQ 3.2) and socioeconomic subgroups (RQ 3.3). Therefore, to answer RQ 3.2 and RQ 3.3., data were first grouped into ten subsets based upon geo-cultural clusters and performed subgroup analysis on each subset using Cox regression (for RQ 3.2). The method was repeated on four socioeconomic subgroups (for RQ 3.3). Next, to understand the interaction of learning design factors with the geo-cultural clusters (and later with socioeconomic clusters), the approach used two-way interaction terms within the regression equation. This empirical approach was used in order to avoid overinterpretation or misinterpretation of subgroup analysis (Lagakos, 2006).

For data management and analysis, Study 3 used R packages `glmnet` and `cv.glmnet`. It is worth noting here that to help in finding important and contributing factors. These packages allow unique variable selection for Cox regression. Regularized-Cox provides various methods. Among other methods (i.e., Ridge-Cox, ElasticNET-Cox etc.), Lasso-Cox has been found to perform better at finding small amounts of signal in data. Therefore, Study 3 used the Lasso-Cox method (by fitting alpha = 1). This method of finding significant interaction has been discussed further in Chapter 6.
3.4.2 Thematic Analysis and Sentiment Mining

Study 4: Thematic analysis and follow up Sentiment mining

Thus far, the overall inquiry relied too heavily on in-situ log data and quantitative methodologies. Hence, in the final phases of this project, Study 4 was undertaken to understand learners’ experiences and views about the various elements of MOOC learning designs rather than distilling this from behavioural and cognitive trace data. Study 4 further evaluated the contextual differences and similarities in learners’ perceptions in relation to their self-reported engagement with the MOOC learning environment. As briefly discussed earlier, this Study 4 was a mixed-method study. The qualitative data were collected using semi-structured interviews and artifact mediated questions. In terms of the adequacy of sample size, it is hard to foreknow how many interviews should be conducted to gain theoretical saturation. Previous research suggests that data saturation can be achieved once around twelve transcripts were (thematic) analysed (see Bryman, 2016; Guest et al., 2012). The qualitative data were then examined to extract the valuable information distinguishable between and within the interview transcripts.

The qualitative data analysis phase is fundamentally about data reduction, a process, as Bryman (2016) stated, 'is concerned with reducing the large corpus of information that the researcher has gathered so that he or she can make sense of it'. There are several methods used to analyse qualitative data, such as grounded theory, critical discourse analysis, qualitative content analysis, and narrative analysis. But thematic analysis by far, is the most common approach used to analyse qualitative data in general and semi-structured interview data in particular (Bryman, 2016; Guest et al., 2012). The following section provides a brief overview of this method used in Study 4.

Thematic Analysis of semi-structured interview data

By definition, thematic analysis is a qualitative data analysis method used for "identifying, analysing, and reporting patterns (themes) within data "(Braun & Clarke, 2006, p. 6). The technique helps to make sense of qualitative data by reporting the experiences and meanings of the participants, often referred to as the reality of the participants (Braun & Clarke, 2006, p. 9). Thematic analysis discovers embedded themes in data items across the entire qualitative data set. A theme represents a patterned response and captures information that prevails throughout the dataset and across multiple data items. The captured information should be crucial and related to the research question(s). Overall, thematic analysis is a useful method to understand the subjective experiences, perceptions and feelings shared by the interviewees (Braun & Clarke, 2006). Rather than merely describing implicit ideas (Guest et al., 2012), in Study 4, the thematic analysis helped cluster the data according to core ideas that emerged from the interviews.
The method comprised six-phased processing of interview data as follows (Braun & Clarke 2006). The first phase involved familiarising oneself with the data where the interview data were read several times to understand the meanings (this critical process is partly the reason why qualitative research uses a relatively small sample size). During the second phase, the data were organised into meaningful and interesting groups called codes. The theme development process is sometimes referred to as coding. The coding process in Study 4 was theory/literature driven and was done using NVivo software. Generally, what a code includes may range from a few words to several sentences, depending on the idea it expresses. In the third phase, the codes were revisited several times to find commonalities and then merged into provisional units of analysis (called themes). The fourth phase involved reviewing and refining the candidate themes that are clear, coherent, yet identifiably distinct. After finalising the meaningful provisional themes that fit together, the fifth phase began. The fifth phase scrutinised the themes further by naming and defining them and identifying their potential to answer the research questions. The sixth and final phase entailed a write-up about a set of fully worked-out themes that were then finally used to address the research questions. The analysis resulted in a set of general codes. At the same time, the research tended to examine similarities and differences in the opinions and perceptions of participants from different geo-cultural contexts.

The analysis was driven by the particular analytic questions where the prevalence of a theme was measured by counting the sources (participants) when it appeared in various data items. Although all counts of prevalent themes are not always necessarily useful in answering the research questions, the individual occurrences of the theme that appeared across the dataset signify predominance. A common approach in thematic analysis, the descriptive coding method, was used. Descriptive coding produces short codes that summarise the primary topic of an excerpt. Similar to descriptive statistics, this coding summarises the qualitative data and provides useful in-depth insights. After first reading through the transcripts, a large number of codes were found. However, only those codes were kept that were linked or related to the overall research problem. In the next iteration of the reading round, several similar codes were combined/clustered, and broader and overarching themes were generated. Finally, a theme level summary was written. To avoid the risk of subjectivity in the generated codes, the analysis was repeated by another expert and one member of the supervision team. Chapter 7, in this thesis, further quantifies and describes in detail the results from Study 4.

Sentiment mining in semi-structured interview data

In semi-structured interviews, the open-ended responses can be relatively ambiguous and can be interpreted in several ways. The response to the ‘why?’ questions in the interview is one such example (see Table 7.1 in Chapter 7). This aspect becomes even more critical when most
interviewees are non-native English speakers, like in the case of Study 4. Since most participants in Study 4 were non-native English speakers (n=16/22, ~ 73%), ambiguous language, technical terms or jargon were avoided in the research instruments. Overall in the interview and artefact in Study 4, the following identical, simple and self-explanatory words were used to probe the participants: enjoyed most (or enjoyed least), liked (or disliked), prefer (or not prefer), favourite, interesting/interested, follow (or do not follow), comfortable (uncomfortable/not comfortable), barrier (not a barrier), or simple phrases such as "Feel [...] to have a positive or negative influence/impact on your learning/engagement with the MOOC/Course content", "contributed towards your learning", "useful for learning", and "supported your learning". The same approach was used during the relatively flexible follow-up "why" questions.

The sentiment analysis (also called opinion mining) method supported understanding the geo-cultural differences in underlying sentiment towards each activity type. The following five types of learning activities were considered for the investigation: articles, videos, quizzes, instructor-led discussion, and user-led discussion. In addition, Study 4 also hypothesised the predictive link between learners' perceived enjoyment and their self-reported current and self-reported future use of MOOC learning resources. Therefore, to further examine the open-ended interview responses, unsupervised sentiment analysis was used.

Sentiment analysis is often referred to as the analysis of affect in text data. Sentiment analysis methods scrutinise the words for positive and negative emotions in the relevant context. In learning analytics, sentiment analysis has widely been used to examine learners' motivation, cognition, engagement, and persistence (for more detail, see D'Mello, 2017; Wen et al., 2014). Study 4 used the R package sentimentr (Rinker, 2017) to approximate the sentiment polarity in the interview transcripts where participants had shared an opinion about one of the learning activity types (i.e., article, video, discussion, quiz). The sentiment polarity was also measured for participants' views about user-led discussions. Finally, the sentiment scores were visually compared for all seven geo-cultural contexts in Study 4 data. The analyses and results are further discussed in Chapter 7.

3.5 ETHICAL CONSIDERATION

This section explains the much-needed compliance of proposed studies with ethical standards. As discussed above, this research aimed to examine to what extent learners' association with a country of a particular geo-cultural cluster influences their processual academic progress in MOOCs. The study tends to explore the potential roles of regional and cultural diversity in learning choices. The overall research examined end-to-end learning processes to understand how different Learning Designs impact, restraint, or facilitate widening participation from all around the globe.
To help maintain a positive and consistent learning experience, FutureLearn encourages research in courses on the understanding that the research follows FutureLearn’s own legal guidelines and research ethics\(^22\). In terms of learners’ data collection, protection, and processing, FutureLearn and its partners stay compliant with the legislation called General Data Protection Regulation (GDPR)\(^23\).

The piece of legislation GDPR came into effect on 25 May 2018, and it deals with how the data is stored, processed, and handled. In order to be used in the partners’ research studies, the FutureLearn data team anonymises the datasets beforehand. As part of setting up the learner’s account, FutureLearn attains the learner’s explicit consent (by ticking a checkbox) to use their data in the research to tailor the services to suit the learner.

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**Figure 3.7** The confirmation email from the OU HREC.

The OU Human Research Ethics Committee (HREC) assessed the research protocol for this research project. The research team were then informed that it does not require an ethics review. Figure 3.15 shows the HREC response and email of confirmation received on 11\(^{th}\) April 2018. (Research-REC-Review application number: **HREC/2842**).

### 3.6 CONCLUSION

This chapter began with the overall philosophical underpinnings of this research, followed by a discussion on the study contexts. The chapter has also provided a brief overview and justification of the (multitude of) methods used in this research. The subsequent four chapters (Chapters 4 through 7) in this thesis describe in detail how the respective methods were utilised to address the research questions. Each of the three chapters will explain the findings and results from the four interlinked studies (Study 1 through 4). Then a final chapter (Chapter 8) concludes this thesis.


\(^23\) [https://gdpr-info.eu/](https://gdpr-info.eu/)
Chapter 4 Role of Learners’ Demographics in Online Learning Outcome (Study1)

This chapter discusses Study 1 from this PhD project. Study 1 seeks to evaluate the dynamic role of six demographic characteristics on academic outcomes in the online learning environment. The first section in this chapter introduces the importance of the topic (4.1). The section that follows (4.2) gives an account of the research questions addressed in this study (RQ 1.1, RQ 1.2). Section 4.3 establishes the context, the methodology and data analysis methods. The following section reports the main results (section 4.4) and a discussion and conclusion (section 4.5). Next, section 4.6 focuses on practical implications and future direction. Finally, section 4.7 seeks to present a link with the subsequent research in this PhD project.

4.1 INTRODUCTION

With the advancements in learning technologies and tools, an immense increase in online learners can be noticed. In recent years, online learning has not only been a viable alternative for learners who were otherwise unable to join a “traditional” face-to-face university but also plays a supportive role in physical classroom-based learning in many developing regions (Zhou, 2016; Bhuasiri et al., 2012; Condie & Livingston, 2007; Veermans & Cesareni, 2005). Online learning is presumably more inclusive, as it allows participants of all ages, gender, and education levels to participate in online learning activities, even those whose performance may be “restricted” by one or the other accessibility needs. Online learning also embraces learners from diverse regional and cultural backgrounds, enabling them to participate and excel in any course from any discipline (Bozkurt & Aydin, 2018; Xu & Rees, 2016; Rutherford & Kerr, 2008). Overall, a large body of research suggests that online learners are characteristically heterogeneous in terms of physical, behavioural, and regional diversity.

The internet era has opened a world of learning opportunities for individuals who want to learn anything, anywhere, and anytime, with few or no restrictions. Despite a growing number of studies exploring various factors related to successful online learning outcomes, very few studies have scrutinized the relationship between learners’ individual characteristics and their learning outcomes as they progress in a course. Previous research in online learning has suggested several factors which may affect learners’ persistence (Hone & El Said, 2016; Greene et al., 2015; Wolff et
al., 2013), type and nature of participation and engagement (Pesare et al., 2017; Nistor et al., 2014; Van Leeuwen et al., 2014; Romero et al., 2013; Rienties et al., 2012), and overall academic performance (Gašević et al., 2016; Tempelaar et al., 2015; Agudo-Peregrina et al., 2014; Huang & Fang, 2013). As discussed in Chapter 2 (section 2.2), these factors include, but are not limited to, individual characteristics, such as the region of origin, age, gender, cultural background; environmental variables, such as poverty level, parental education, nature of employment; academic characteristics, such as level of education, previous educational outcomes, distinct approaches towards studying; and learning environment variables, such as learning design, learners’ interactions with other learners or with learning resources. In the remainder of this chapter, six of these factors were brought together under the umbrella term of demographic characteristics.

With its origin in the Greek language, the literal meaning of the word demography is ‘description of the people’. However, in statistics, demographics refer to the quantifiable characteristics of a given population (Rowland, 2003, p. 16). An emerging body of research has explored how demographic characteristics may influence learners’ behavioural patterns and cognition in online learning environments (Cai et al., 2016; Kizilcec & Halawa, 2015; Kuzilek et al., 2015; Morris et al., 2015; Ke & Kwak, 2013; Nistor, 2013; X. Liu et al., 2010; Tapanes et al., 2009). However, most recent studies used either one or a combination of very few learning and learner characteristics to implicate the risks involved in retention or performance (see Chapter 2, section 2.2 for more details). From the literature, a few of the most pertinent factors include socioeconomic status (Reich & Ruipérez-Valiente, 2019; Stich & Reeves, 2017), employment status (Diep et al., 2016; Wladis et al., 2015), gender (Boyte-Eckis et al., 2018; Cai et al., 2017; Kizilcec et al., 2017), age (Boyte-Eckis et al., 2018; Kizilcec et al., 2017; Ke & Kwak, 2013; Nistor, 2013) and disability status (Muilenburg & Berge, 2005; Richardson, 2009, 2015). Likewise, other demographic information has also been used to predict learners’ performance, such as education level (Kizilcec et al., 2017; Diep et al., 2016) and geographical location (Bayeck & Choi, 2018a; Nistor, 2013).

Recent LA and EDM literature have begun to focus on employing one or several demographic characteristics discussed above. However, learners’ behaviour at a particular point in time, such as during the first week, has mostly remained a focal point (Allione & Stein, 2016; Jiang et al., 2014). When researchers observed behavioural changes over time (see, for example, Nguyen et al., 2018; Kloft et al., 2014), they mainly relied on engagement history or clickstream information from a respective week. In the process, they mostly steered clear of ample data that are either readily available or easily collectable from online learners, such as learners’ age, gender, and education level. Most research to date has presented a more generic view using either descriptive statistics or advanced predictive modelling techniques. Although such work may have employed various
demographic characteristics, among other learning-related variables, to predict the temporal online academic performance accurately. Whether predictive links vary across courses from distinct disciplines has received limited empirical attention. Therefore, a comprehensive understanding would require much research into the “dynamic” role of demographic variables on online learners’ performance over time. This background raises the question on how a large set of individuals’ contextual or demographic characteristics can be used to investigate their association with the performance in online learning environments.

It is important to note here that predictive modelling can be used for two related purposes. First, to perform predictions leveraging a set of variables from the data. Second, to explain the association between a given set of variables and a particular outcome. Predictive model development focuses on making accurate predictions using any kind of information available at hand. While at times, theoretically important or scientifically meaningful variables may be excluded if they add no predictive benefits.

In contrast, explanatory models’ primary aim is not to accurately predict the outcome per se but to evaluate and understand the predictive link between the outcome and the given set of variables. The set of variables should be theoretically or scientifically meaningful in the given context, and the analyses are generally more interpretable. A predictive model fits all useful predictors intending to improve model accuracy. On the other hand, an explanatory model uses the same predictive methods, generates moderate accuracy, but fits theoretically essential variables and focuses more on a theoretically meaningful relationship with the outcome (for more detail, see Liu & Koedinger, 2017).

Study 1, therefore, used classification modelling to explain the dynamic role of demographic characteristics in successful online learning, an approach sometimes referred to as explanatory modelling (see also section 3.4 in Chapter 3). Study 1 is the first attempt in this direction as, firstly, it covers a large sample of learners enrolled in online courses from different disciplines at the OU, UK. Secondly, this research takes into consideration a large set of potentially explanatory demographic variables. Lastly, using advanced classification techniques for dynamic predictions, Study 1 examines whether, and how, six demographic characteristics (i.e., region of origin, multiple deprivation level, educational background, age group, gender, and disability status) are associated with the outcomes of online assignments over time. The empirical approach used in Study 1, helped to compare the contribution of learners’ characteristics across four different courses and learning designs. The study tested the significance of these factors’ contribution to model learning outcomes.
The following section aims to develop research questions RQ 1.1 and RQ 1.2 driven by the previous work. As discussed earlier, all six of these key characteristics listed in the research questions have been shown to influence online academic performance.

4.2 PURPOSE OF MAIN STUDY AND RESEARCH QUESTIONS

The studies mentioned in the literature review (Chapter 2 in this thesis) used various statistical and machine learning methods to predict at-risk learners or overall learners’ achievement in online or blended learning. Still, the predictive accuracy and interpretability of such models remained primarily dependent upon the respective data sources, the nature of the predictor variables, and the underlying methods. Within this aforementioned body of literature, individual demographic characteristics are widely used either as one of predictors or as control/moderating variables.

Most of the models in previously described literature only used one or a couple of these characteristics; hence may have under- or overestimated the impact of individual differences on online learning outcomes. Existing literature on performance prediction (Kizilcec et al., 2017; Allione & Stein, 2016; Kuzilek et al., 2015) recognises that along with other predictors such as engagement history or social interactions, the inclusion of one or few demographic variables offers a potential to increase the predictive model accuracy significantly. Yet, it can be noticed that some of the discrete features, for example, disabilities or specific regional belonging, were scarcely employed in the modelling process.

This research gap raises concerns that if introducing such individual variables can increase model accuracy, can these variables alone be used in an explanatory model to predict learners’ performance in course assessments? As mentioned earlier, some researchers have examined learners’ performance at different points in time (Allione & Stein, 2016; Jiang et al., 2014). However, there is still uncertainty about whether these characteristics can influence learners’ performance temporally, throughout the course, and in course assessments, at different points in time? These concerns led us to RQ 2.1, which deals with the nature and temporality of the association of demographic characteristics with learning outcomes. The question also refers to developing a self-explanatory classification model to understand such association (if any). To increase the proposed approach’s generalizability, it needs to be tested across various disciplines. That raises the question of how to accommodate such a large number of demographic variables as predictors of multiple academic success levels or success in different disciplines? This question has shaped RQ 1.2 in the current study.

Against this background, Study 1 proposes a way to predict online learning outcomes based on the six demographic characteristics discussed in the literature review. It also finds the relative significance of each of these variables towards the model building, using data from 8,581 learners.
across four online courses at the OU. Most empirical studies have primarily predicted whether learners would pass/fail a course (Mueen et al., 2016; Agudo-Peregrina et al., 2014; Huang & Fang, 2013). But in Study 1, successful online learning outcomes are defined not solely by passing the course but on whether a learner is passing the subsequent assignments within a course. An additional innovative feature beyond combining a range of demographic characteristics is that it also included a range of assessment performances using the same predictor variables. These course assessments were conducted at different points in time throughout the semester. The researcher remained particularly interested in whether demographic characteristics might have a temporary or sustained association with academic performance over time. If such association confirms to be true, can we list down or rank these factors as per their contribution, or in other words, importance, towards a more elaborative model development. Against this background and based on the literature review presented in the previous sections, the following research questions are proposed.

**RQ 1.1** To what extent is there an association between learners' demographic characteristics (i.e., Regional context, Socioeconomic context, Education, Age, Gender, and Disability) and online learning outcomes throughout the online course?

**RQ 1.2** To what extent does the association (from RQ1.1) varies across different online courses with distinct learning designs?

### 4.3 METHODS

#### 4.3.1 Context and Data Pre-processing

The OU is the largest university in the UK and Europe. So far, more than 170,000 learners have studied at the OU. It is worth highlighting that, like MOOCs, the OU offers an open entry policy where anyone can start a degree irrespective of previously acquired qualifications. All courses are offered via university’s virtual learning environment (VLE). The learners provide information on learners' background and demographics during the registration process when they enrol for one or more courses. This information is stored in the university’s management information system.

A recent OU research project called the OU Analyse has focused on improving online learning experiences by providing informed guidance to the learners and optimising learning materials. One part of OU Analyse dealt with collecting and analysing learners’ data stored in the system. As a result, the project produced a set of publicly available, anonymised datasets; the OU Learning Analytics Dataset (OULAD) (Kuzilek et al., 2017) (see section 2.4.1 in Chapter 2 for more detail). These anonymised datasets comprise learner information and clickstream data when learners interact with the VLE as well as the course assessment outcome (Kuzilek et al., 2017). As part of the formal registration process, learners are informed about the university's Data Protection Policy and
Policy on Ethical use of Learner Data for Learning Analytics (LA); both cover essential information regarding their personal data usage. Anonymisation of data is performed in a series of steps, and the overall process has been designed in accordance with the ethical and privacy requirements applied at the OU (compliant with the UK Data Protection Act and GDPR). The OULAD creation and release process had been closely supervised by the OU management and approved by the Vice-Chancellor Executive Committee.

Previously, in a large scale study, Kuzilek et al. (2015) have analysed several of these OULAD datasets intending to provide early prediction of ‘at-risk’ learners based upon a range and combination of some demographic variables (i.e., gender and education) and learners’ VLE history. Study 1 in this thesis used a sufficiently large subset of OULAD datasets for UK based learners and the original sample comprised 8,581 learners. This subset of OULAD dataset contained information about several OU courses offered in 2013 and 2014. To answer RQ 1.1, datasets for two offerings of a single course A were used. To address RQ 1.2, single offerings of each of four courses A, B, D and E, were used. These four selected courses are large-scale introductory courses across various disciplines at the OU (that is, Health and Social Care, Science, History of Europe, and Engineering). These representative courses typically are of interest to all learners who follow a particular specialization (e.g., Engineering), and are jointly decided by course teams who work across a range of further follow-up courses.

Table 4.1 Students’ Distribution and Pass Rate

<table>
<thead>
<tr>
<th>Course</th>
<th>Name (Discipline)</th>
<th>Year</th>
<th>Enrolled Students</th>
<th>Pass Rate (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>History of Europe</td>
<td>2013</td>
<td>383</td>
<td>79.88</td>
</tr>
<tr>
<td>B</td>
<td>Health and social care</td>
<td>2014</td>
<td>3905</td>
<td>57.50</td>
</tr>
<tr>
<td>D</td>
<td>Science</td>
<td>2013</td>
<td>3241</td>
<td>55.78</td>
</tr>
<tr>
<td>E</td>
<td>Engineering</td>
<td>2013</td>
<td>1052</td>
<td>59.58</td>
</tr>
</tbody>
</table>

Academic retention is a key concern for many online learning institutions, and in particular at the OU. Among those who completed the course and attempted the final exam in 2013 or 2014, pass rates ranged between 55% and 80%. However, these figures do need to be read in the context of the OU’s mission to provide education for all, regardless of entrance requirements. Table 4.1 summarises the data of enrolled learners in the four courses in the year 2013 and 2014. As part of the selection criteria, only those learners were included who were residing in the UK at the time of

25 After attaining access to the FutureLearn data, and receiving ethical approvals from the OU ethics committee, as well as the FutureLearn, the investigation was further replicated over ten FutureLearn MOOCs, whereby the results remained comparable.
enrolment and whose demographic information was complete. These learners never got unenrolled from the respective courses; they consistently participated in the course and attempted the final exam. Our final analysis found 3,908 consistent learners across the four courses.

4.3.2 Variables

In line with the literature review, Study 1 focused on six demographic characteristics as potential academic performance predictors. For each learner, six data points \((x_1, x_2, \ldots, x_6)\) were extracted. All variable levels and categories were renamed to make them more comprehensible when they appear in a decision tree (see Appendix B, Table B 4.1 to B 4.4). The variables are described as follows:

- \(x_1\): Region: Identified the geographical region within the UK, where the learner lived while taking the course.
- \(x_2\): IMD_band: Specified the Index of Multiple Deprivation Band for the place where learner lived while taking the course. The band represented the neighbourhood poverty level.
- \(x_3\): Education: Indicated the highest level of education on entry to the course.
- \(x_4\): Age: Identified the age band for each learner.
- \(x_5\): Gender: Gender of the learner.
- \(x_6\): Disability: Indicated whether the learner declared a disability.
- Response Class Y: Distinction, Pass, Fail. [in TMAs: Distinction \(\geq 85\), Pass \(\geq 55\), Fail < 55]

As reported in Appendix B and section 3.3.2 in Chapter 3, the UK was divided into 13 regions as follows: East Anglian, East Midlands, Ireland, London, North, North Western, Scotland, South East Region, South, South West, Wales, West Midlands, and Yorkshire. Regarding learners’ geographical location within the UK, only 6 % of learners belonged to Ireland, whereas the largest number of learners (13 %) were situated in Scotland. While in relation to the socioeconomic background, datasets used the Index of Multiple Deprivation (IMD) to identify learners who belonged to deprived areas. At the time of enrolment, almost 9 % of overall learners were classified as relatively underprivileged.

Learners’ minimum education level was reported as no formal qualification, lower than A level, A level or equivalent, higher education qualification, and postgrad qualification. Here A level (Advanced level) or equivalent is a secondary school leaving qualification, generally required for university entrance. Lower than A level represents those who never acquired A level qualification. Higher education qualifications in the UK are degrees, diplomas, certificates, and other academic awards granted by a university or higher education college. In our sample, the vast majority of learners had a qualification at A-level or equivalent (46 %).
Regarding age and gender, learners belonged to one of three age bands A1 (less than or equal to 35 years), A2 (36 to 54 years), or A3 (55 years or more). Our sample contained a relatively young adult distance learner, with 68% of learners under 35 years, and only 1% were above 55. As for gender distribution, 52% of learners were female. Additionally, almost 7.47% declared some kind of disability.

In order to address RQ 1.1, predictive models were used to forecast the learning outcomes of five Tutor Marked Assessments (TMA1 – TMA5) and a final exam for Course A. The reason for focusing first on Course A was learners’ consistent participation and the lowest withdrawal rate (only 16.84%), which allowed us to use the richest data set first to explore in our model. For RQ 1.2, i.e., to investigate if the method is useful for other courses, outcomes of final exams in the remaining three courses were predicted. The study selected data for those learners who had completed their semester and appeared in the final exam to maintain consistency.

4.3.3 Data Analyses
Study 1 employed a supervised learning method called Decision Trees, often used for nominal classification. The classification models were developed into two phases. In the first phase (Figure 4.1), six different predictive models (S1 to S6) predicted the outcome of five Teacher Marked Assignments (TMA1 to TMA5), and one FINAL RESULT for Course A. Figure 4.1 shows a simplified view of these six predictive models. For Phase 1, records of 289 learners from the first course offering were used. Furthermore, model consistency was evaluated using the dataset from the next offering of the course in 2014. The model seemed to be successfully consistent within the same course.

Figure 4.1 Phase 1: Classification models to predict learning outcome of TMA1-TMA5 and FINAL RESULT.
As illustrated in Figure 4.2, Phase 2 successfully repeated the development of predictive models to predict overall learning achievement (i.e., FINAL RESULT) for three more courses offered by OU (Course B, D, and E). Analyses in Phase 2 were an attempt to examine whether and how the role of six demographic characteristics was pertinent in various online courses.

Figure 4.2 Phase 2: Classification models to predict FINAL RESULT of courses A, B, D, E.

Both modelling phases aimed to explore the importance of different characteristics when they contribute to the model building by creating and visualising DTs. The rpart() package from R was used for the analyses. The package implements CART (Therneau et al., 2010), and is often used to produce recursive partitioning in classification, regression, and survival trees. This R programming package provides variable importance, a named numeric vector that unfolds each variable’s importance (if there are any splits for tree development). When printed by the summary, the importance of each variable is rescaled to add to 100. According to Therneau et al. (2010), this technique identifies the essential variables for successful tree-based classification and indicates each variable’s importance in the present data. Moreover, rpart() uses k-fold cross-validation to validate the optimal cost complexity parameter (cp).

The confusion matrix, also known as an error matrix, describes a classification model performance. The confusion matrix table consists of true predictions and prediction errors (Figure 4.3). Overall accuracy, precision, and recall were calculated as prediction accuracy criteria for this n-class classification problem, where n = 3 represents a three-class problem, namely D = Distinction, P = Pass, F = Fail.
With the help of a confusion matrix for each model, Prediction accuracy, Precision, and Sensitivity were calculated using the following criteria:

- **Overall Accuracy** = \(\frac{TP_D + TP_F + TP_P}{TP_D + TP_F + TP_P + E_{DF} + E_{DP} + E_{FP} + E_{PD} + E_{PF}}\)
- **Precision** \(_{\text{Distinction}}\) = \(\frac{TP_D}{TP_D + E_{FD} + E_{PD}}\)
- **Sensitivity: Recall** \(_{\text{Distinction}}\) = \(\frac{TP_D}{TP_D + E_{DF} + E_{PD}}\)

In the model, the overall accuracy indicates how well a model predicts learners’ academic performance. It represents how often the classification model was correct. This measure is typically calculated as the sum of correct classifications divided by the total number of classifications. Precision indicates that when a class was predicted, how many times in total prediction of that class, the system was in fact, correct. This measure is calculated by dividing the TP of the corresponding class with the sum of the corresponding column in the confusion matrix. The recall represents the sensitivity of the classification model and is also called the true-positive rate. Recall indicates that when a certain class should have been predicted, how many times it actually happened to be correctly predicted. This accuracy measure is calculated by dividing the TP of the corresponding class with the sum of the corresponding row in the confusion matrix.

### 4.4 RESULTS

**Phase-I: Model development for RQ 1.1**

The initial model building was conducted using training data of 200 records (≥70%) of Course A. Afterwards, a dataset of 89 records were used as test data to calculate accuracy measures. As an example, Figure 4.4 represents the confusion matrix for step S6 in the phase1.
Since this is a three-class classification problem, precision and recall were calculated separately for each class. Overall accuracy was also computed for each step from S1 to S6 (Table 4.2). Overall accuracy ranged from 66.29 to as high as 83.14; however, at some points, the models appeared to be inadequate or unable to predict Distinction and Fail correctly, as indicated in Table 4.2. It is important to note that these explanatory results show a potential trade-off between getting benefit from interpretability of DTs, and predictive accuracy for underrepresented classes (in this case, Distinction and Fail).

To examine the extent of potential association (RQ 1.1), the importance of each of the six demographic variables was listed down and compared as per their contribution towards model development. The predictive models were given input of all six predictor variables, and for each predictive model, variable importance was evaluated (See Table 4.3). Throughout the modelling, certain variables were found to be contributing more than others. For instance, Region and IMD band were found to be the most critical predicting variables among all, offering useful explanatory details. Both variables had a comparable significant influence on tree induction.

<table>
<thead>
<tr>
<th>Steps</th>
<th>Overall Accuracy</th>
<th>Precision (%)</th>
<th>Recall (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Distinction</td>
<td>Fail</td>
</tr>
<tr>
<td>S1</td>
<td>74.16</td>
<td>25.00</td>
<td>14.28</td>
</tr>
<tr>
<td>S2</td>
<td>76.11</td>
<td>25.00</td>
<td>33.33</td>
</tr>
<tr>
<td>S3</td>
<td>75.28</td>
<td>25.00</td>
<td>0.00</td>
</tr>
<tr>
<td>S4</td>
<td>66.29</td>
<td>0.00</td>
<td>28.57</td>
</tr>
<tr>
<td>S5</td>
<td>75.28</td>
<td>12.50</td>
<td>0.00</td>
</tr>
<tr>
<td>S6</td>
<td>83.14</td>
<td>25.00</td>
<td>33.00</td>
</tr>
</tbody>
</table>

Table 4.2 Accuracy, Precision and Recall for Predictive Models of Course A
Variable importance for the variable Region, ranged between 28 and 49 (average = 38.83), while for IMD band this ranged between 25 and 39 (average = 28.33). The third and fourth most important variables were found to be Education and Age, with average importance of 17.17 and 15.20, respectively. The results indicated that Gender and Disability had the least significant effect on tree induction. Graphical illustrations (see Figure 4.5) were particularly useful to understand the role of each predictor variable. To examine the temporal dynamics, six predictive models were trained to predict the outcomes of five assessments (TMA1 to TMA5) offered at different points in time along with the final exam outcome. Figure 4.5 draws the importance or the contribution of each variable on a scale of 0 to 100.

<table>
<thead>
<tr>
<th>Steps</th>
<th>Feature</th>
<th>Region</th>
<th>IMD</th>
<th>Education</th>
<th>Age</th>
<th>Gender</th>
<th>Disability</th>
</tr>
</thead>
<tbody>
<tr>
<td>S1 (Acc = 73.0)</td>
<td></td>
<td>29</td>
<td>26</td>
<td>44</td>
<td>-</td>
<td>-</td>
<td>1</td>
</tr>
<tr>
<td>S2 (Acc = 75.0)</td>
<td></td>
<td>32</td>
<td>32</td>
<td>10</td>
<td>22</td>
<td>4</td>
<td>-</td>
</tr>
<tr>
<td>S3 (Acc = 75.2)</td>
<td></td>
<td>44</td>
<td>23</td>
<td>10</td>
<td>22</td>
<td>-</td>
<td>1</td>
</tr>
<tr>
<td>S4 (Acc = 66.3)</td>
<td></td>
<td>49</td>
<td>23</td>
<td>5</td>
<td>21</td>
<td>-</td>
<td>2</td>
</tr>
<tr>
<td>S5 (Acc = 75.3)</td>
<td></td>
<td>43</td>
<td>39</td>
<td>10</td>
<td>2</td>
<td>5</td>
<td>1</td>
</tr>
<tr>
<td>S6 (Acc = 83.1)</td>
<td></td>
<td>37</td>
<td>28</td>
<td>23</td>
<td>9</td>
<td>1</td>
<td>2</td>
</tr>
</tbody>
</table>

In other words, the main result for RQ 1.1 was a clear and strong link between the six variables of interest and academic outcomes. It is also apparent that in the development of predictive models, the demographic variables’ contribution varied temporally. From one assessment to the other, the demographic variables influenced the predictive model development differently. As illustrated in Figure 4.5, Region and IMD had a consistent impact on assessment outcomes. At the same time, prior knowledge (i.e., Education) was critical for the first TMA, but the effect faded over time. The findings might indicate that learners with lower prior qualifications could successfully overcome their initial disadvantage if they continued to participate in the course. Nonetheless, Region and IMD differences remained pertinent, as highlighted by other research on the impact of socioeconomics on learning outcomes (Wladis et al., 2014; Walpole, 2003).

To evaluate replicability, records of 299 learners were used from the next offering of the same course in 2014. The model seemed to be consistent with an accuracy of 70.23%. A potential reason for this reduction in overall accuracy may be due to a large test set (299 records) compared to the test set used in the first offering in 2013 (89 records). However, accuracy was high enough to confirm model consistency.
Follow-up DTs visualisations in Figure 4.6 indicated that in Step 1, learners with a postgraduate qualification may potentially attain a distinction in TMA1. A learner without a postgraduate qualification, if residing in the North or South East region, with the IMD band rating of either L3 or L5, is also likely to distinguish in TMA1. Therefore, the results also suggested that elaborative predictive models can be developed using demographic variables with varying degrees of accuracy. Besides, the associations were found to be temporal in nature, which changed throughout the course. From DTs in Figure 4.6, associated rules could be extracted and used to analyse the resulting patterns in detail. The following section explains how to read and draw out information from a typical DT.

Classification Rules and Information Extraction from DTs

In decision trees, each path from the root to a leaf represents a rule that can infer class membership (see Breslow & Aha, 1997). Naturally useful in explanatory modelling, a rule provides a detailed explanation for a classification query and can help extract useful information from the DTs. For example, using Figure 4.6, one can derive the following classification rule for model S4 (Phase 1):

IF [Region=L, N, SE, S, SW, W, WM, Y] AND [IMD = NA, L2, L4, L6, L10], THEN Outcome = Pass

It is important to note here that when deriving such rule, the left-hand side or antecedent is the path and the right-hand side or consequent is the conclusion represented as a leaf in the tree,
containing a class label. As mentioned elsewhere, the algorithm breaks down the dataset into smaller and smaller subsets. The final results are incrementally developed, flowcharts like a tree with decision nodes and leaf nodes. Each decision node has two (i.e. Yes and No) or more branches, representing a “test” on a variable. The leaf node denotes a classification or decision for the respective path (in this case, the decisions or assigned classes were Pass, Fail or Distinction).

For example, the root decision node in step S2: Age = A3 has two branches with yes and no, representing learners who belong to age band A3 (yes) or those who do not belong to age band A3 (no). In other words, those who were 55 years old or more (yes, branch) were more likely to get a Pass result. To put this into context, the following is an explanation of step S2 in Figure 4.6. Step S2 predicted the outcome of the TMA2 assessment, and it can be gathered that if the learner belonged to Age band A3 and was not from IMD band L9, L10, then that learner will most likely get a Pass grade.
Figure 4.6 Predictive models for course A (2013).
Phase-II: Predictive Modelling for RQ 1.2

The similar modelling exercise was repeated for three courses from different disciplines and appeared to be successful in most cases (see Table 4.4). Yet again, Region, IMD, and Education were significant and contributed most towards the model-building to predict FINAL RESULT.

Table 4.4 Variable Importance (Phase 2)

<table>
<thead>
<tr>
<th>Steps</th>
<th>Feature</th>
<th>Region</th>
<th>IMD</th>
<th>Education</th>
<th>Age</th>
<th>Gender</th>
<th>Disability</th>
</tr>
</thead>
<tbody>
<tr>
<td>A2014J</td>
<td>Region</td>
<td>36</td>
<td>33</td>
<td>17</td>
<td>7</td>
<td>4</td>
<td>3</td>
</tr>
<tr>
<td>B2014J</td>
<td>Region</td>
<td>39</td>
<td>32</td>
<td>20</td>
<td>9</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>D2013J</td>
<td>Region</td>
<td>40</td>
<td>16</td>
<td>42</td>
<td>-</td>
<td>2</td>
<td>-</td>
</tr>
<tr>
<td>E2013J</td>
<td>Region</td>
<td>34</td>
<td>23</td>
<td>30</td>
<td>11</td>
<td>2</td>
<td>-</td>
</tr>
</tbody>
</table>

Somewhat surprisingly, IMD had a relatively large impact on Course A and B, while for Course D and E this was a weaker factor. In contrast, prior Education had a relatively significant role in Course D and E, while somewhat smaller for Courses A and B (see Figure 4.7). In terms of Age, all models except for Course D were indeed influenced by age, whereby in all courses except Course A (History of Europe) there was a larger population of young learners (age band 0-35 years). Concerning the role of gender, a small but significant association was found for three courses, A, D and E. Finally, disability had no significant contribution towards the prediction of learning outcomes, except for Course A.

![Graphical representation of Variable Importance](image-url)

**Figure 4.7** Graphical representation of Variable Importance [RQ 1.2].
4.5 DISCUSSION AND CONCLUSION

Model Evaluation and Limitations

Despite the ease of access and intrinsic diversity in online learning, there are very few studies that inquire about the impact of wide-ranging demographic characteristics on a relatively large scale. Previous literature (Boyte-Eckis et al., 2018; Stich & Reeves, 2017; Kizilcec et al., 2017; Nistor, 2013) has already suggested some influence of particular individual demographic characteristics on success in online learning. Study 1 is among the first to empirically test the overall association and relative importance of a large number of demographic variables on successful learning outcomes over time while using an extensive, wide-reaching sample of four online courses offered at the OU. Study 1 has provided strong evidence that specific demographic characteristics (i.e., Region, IMD) can contribute more when used in predicting learning outcomes. In contrast, others (e.g., gender, disability) did not significantly influence learning outcomes in DT based explanatory modelling. The study used decision tree algorithms for classification and prediction, and like any other multiclass classification problem, precisions and recalls were calculated separately for each class, whereby overall models’ accuracies varied between 66.29% to 83.14%. The model accuracy was confirmed first longitudinally on the next offering of the same course and subsequently across three other courses. The overall results were found to be consistent with a varying degree of accuracy.

In Study 1, RQ 1.1, aimed to examine the nature and extent of the association between demographic characteristics and successful online learning at various junctures. The investigation was started with a single OU course. The most important findings were in line with previous research (Wladis et al., 2015; Guo & Reinecke, 2014; Nistor, 2013; Richardson, 2009; Christie et al., 2004; Walpole, 2003), providing empirical evidence that the Region of origin and socioeconomic indicators (such as IMD band), were consistently strong and interesting predictors. These two variables were the most contributing factors in most decision tree inductions. Likewise, Region and IMD can successfully predict learning outcomes of assessments conducted at different points in time throughout the course.

One potential reason why Region might have had such a strong impact is related to the socio-geographic division of regions in the UK, and its related educational systems. For example, learners at OU Scotland can study for free, while learners in England have to pay around £5000 per year to study. Similarly, as previously mentioned (Smith et al., 2015; HEFCE, 2014), there are substantial socioeconomic differences within the UK, whereby the south of England and London are more affluent and higher educated than the other regions. Furthermore, as indicated by Kizilcec et al., (2017) and Walpole (2003), learners with lower socioeconomic status are more likely to struggle in higher education, which was supported in Study 1.
In contrast with HEFCE (2014) and others (Kizilcec et al., 2017; Diep et al., 2016; Richardson, 2009), the second finding was that prior education level generally was a less prevailing feature, especially in comparison to Region and IMD. One reasonable assumption might be that prior education may contribute towards achievements in the first few assessments, as was noticed in Phase-I analysis. However, as the course progresses, other factors become imperative, and the importance of prior education declines as a contributing factor towards subsequent achievements in the online learning environment. This links well with previous research that has used more dynamic data analyses to predict performance (Tempelaar et al., 2015), whereby actual engagement in a course, as well as cognition were found to be more important predictors than “static” variables, like demographics and prior education.

Interestingly, age has long been perceived to be negatively correlated with online participation and learning, but in line with others (Diep et al., 2016; Curşeu, 2013; Richardson, 2013; Ke & Kwak, 2013; Ke & Xie, 2009) a small significant effect of age was noticed on overall learning outcomes. It is noteworthy here that as the online course advanced, Age became a more influencing variable in the predictive model than prior education. This also supports the suggestion of Diep et al. (2016) on how researching different critical age ranges may yield a better understanding of overall impact, as online learning can be a desirable learning format for adult and lifelong learners.

Since online participation (Boyte-Eckis et al., 2018; Nistor, 2013), social interaction (Kizilcec et al., 2017; Diep et al., 2016) and learning achievements (Yukselturk & Bulut, 2009a; McSporran & Young, 2001) differ for male and female; one can assume that gender may play a significant role in online learning. Rather surprisingly, Gender was consistently a trivial factor in decision tree induction. These results were dissimilar to other researchers (Diep et al., 2016; Nistor, 2013; Richardson & Woodley, 2003; McSporran & Young, 2001), concluding minimal predictive link and offering negligible explanatory power.

Disability was the least significant variable throughout, which slightly reaffirmed previous findings (Jelfs & Richardson, 2010; Richardson, 2009, 2015). These findings contradicted previous studies such as Cooper et al. (2016) and Muilenburg & Berge (2005) on how numerous challenges students face with some kind of disability might affect their accomplishment level in the online learning environment. At this point, it is worth mentioning a limitation that there was a relatively small presence of disabled learners in our overall data sample (~7.5%), highlighting the fact that further research with a larger disabled population may potentially yield different results.

Addressing RQ 1.2, i.e., if the proposed approach presented in RQ 1.1 would fit in all instances and can be used in other circumstances within different courses, the exploration was reiterated on other courses offered at the OU. To have a better understanding, the results were compared from different courses. Notably, IMD had a larger impact on course A and B, whereas a slightly lower
impact of IMD was reported on courses D and E. The effect was reversed in the case of prior education.

A potential reason for this might be related to the nature of the course discipline, whereby Course A and B are nested in the “softer” sciences, while Course D and E are introductory courses to hard sciences and might thus attract a different type of learners. Also, it was noted that in Course D and E, learners with higher education comprised a relatively larger proportion in the overall population. This cross-course explanatory analysis revealed that performance in nearly all courses was minimally affected by Age. Even a presence of elderly population in Course A did not affect the relevant model considerably. Similarly, Gender remained unimportant in the overall tree induction process, specifically in case of course A, D and E. Given that Course B (Health and social care) is a course with large numbers of women (> 88 %), perhaps this was less prevalent. Disability again, with a negligible exception of Course A, failed to alter any of the classification models in this second phase of experimentation. In other words, these findings indicated that Region and IMD of learners had a significant predictive association with academic achievements, while the relative contribution of these factors in part were related to the respective course, indicating a possible multi-level effect that merits further research.

In conclusion, research has shown online learners’ performance to have an association with their demographic characteristics, such as regional belonging, socioeconomic standing, and education level, age, gender, and disability status. Despite a growing number of studies exploring factors for successful online learning outcomes, most researchers have utilised one or a combination of very few learner characteristics. Moreover, a limited number of studies scrutinised the impact of individual characteristics on learning outcomes as learners progress in a course. Study 1 in this thesis investigated and compared the dynamic influence of six demographic characteristics on online learning outcomes using a sample of 8,581 UK based learners across four OU online courses from four different disciplines. Among other variables, region, neighbourhood poverty level, and prior education were strong predictors of overall learning outcomes. However, at a fine-grain level, such influence varied temporally as the course progressed, as well as between different courses. All in all, this means that our findings were in line with Diep et al. (2016) and Gašević et al. (2016) advocating that generalization of results, even for individual courses, should be used with caution, supporting the need to adapt for a wider trend. The findings are suggestive of inclusion of demographic variables (such as region of origin, socioeconomic status, prior education, etc.) in such predictive modelling in EDM and Learning Analytics.

Even after attaining reasonable accuracies, there were some limitations attached to the approach discusses in Study 1. First, it was noted that almost all predictive models were biased towards the majority class; Pass in this case (Distinction = 6.9%, Fail= 6.5%, Pass=86.6%). The phenomenon is
natural for decision tree based predictive models. Henceforward, to prevent the bias from arising in the first place, future research could be conducted using methods that mitigate the skewed class bias like under-sampling the large class or over-sampling the small class. A similar caveat attached to this approach is another algorithm-specific constraint. Although DTs based methods may produce excellent explanatory models, the tree induction may occasionally be biased towards variables with large number of distinct values.

Second, a change in accuracy measures, from overall accuracy to weighted accuracy for example, may also help to understand and evaluate the predictive models. Third, Study 1 was aimed at finding the role of six demographic characteristics only. In addition, other relevant variables (e.g., parents’ education, employment status) could also be used in different combinations to improve accuracy and consistency of practical and implementable predictive models. One good example could be an extension of the previous work of Kuzilek et al. (2015), where along with other performance and engagement variables, they used two demographic variables (gender, education). Although the findings have broader implications, it should be acknowledged that these analyses were conducted using data from UK based learners only. Last, Study 1 reported the relationship between the learning outcomes and the demographic characteristic variables when these variables contributed toward tree induction, although these inductive powers did not represent causes. Therefore, further research is needed to understand the causation behind these relationships.

4.6 LINKS WITH OTHER STUDIES IN THIS THESIS

The findings from Study 1 indicated that learners’ region and socioeconomic status had a significant predictive association with their academic achievements, while the relative contribution of these factors remained related to the respective course with a distinct learning design. While Study 1 was useful for understanding the predictive role of learners’ characteristics in online learning outcomes, a major limitation of Study 1 was that it focussed on formal learners attending a formal qualification at one distance learning provider. Furthermore, most of the learners involved in Study 1 were from the UK, whereby this thesis aims to explore how learners across the globe engage in an informal online learning environment such as MOOCs.

As this thesis is specifically focused on diversity and inclusion in open online learning designs, it still needs to be verified whether the modelling approaches and outcomes provided in Study 1 make sense in the context of informal learning, in particular for MOOC learners from different geo-cultural and socioeconomic backgrounds. This has led to Study 2 (Chapter 5), which explores the link between learning processes and learning design in a FutureLearn MOOC, and then in various geo-cultural and socioeconomic contexts. The result from Study 1 also laid the foundation for the research problem addressed in Study 3 (Chapter 6), which examines if variations in learning design are linked with learners’ persistence in dissimilar contexts.
Chapter 5 Variations in Learning Processes and Activity Engagement (Study 2)

As discussed in Chapter 3, this thesis covers four distinct yet linked studies. This chapter explains Study 2 in this project. Study 2 aims to explore the variations in learning processes and activity engagement behaviour in a MOOC\textsuperscript{26}. Since regional and socioeconomic backgrounds were found to be two important factors linked with online learners’ progress (see section 4.4 in Chapter 4), this exploratory Study 2 further examines the differences in the activity engagement behaviour in various geo-cultural and socioeconomic contexts in the informal MOOCs learning. While Study 1 found strong empirical evidence for the role of regional and socioeconomic contexts, the approach failed to address many aspects of learning designs, such as various types of learning activities and the predetermined order of those activities. Another obvious limitation of Study 1 was that it was conducted in the formal learning environment. Moreover, the empirical modelling used in Study 1 primarily emphasised on online learning outcome, without taking into consideration the underlying learning processes in the respective courses. Therefore, Study 2 specifically focused on the learning processes and learners’ engagement with various learning design elements. In the process, the Study 2 investigates the prevalence of contextual differences in learners’ engagement behaviours.

Section 5.1 in this chapter introduces the rationales behind Study 2, leading to section 5.2 that summarises the research questions. Section 5.3 describes the study methodology, including the context and data pre-processing. The same section discusses data analysis methods used to address each research question. Section 5.4 presents results followed by a brief discussion (section 5.5). The section 5.5 also offers explanations for the findings while concluding the chapter. Finally, section 5.6 gives an account of how this exploratory study sets the foundation for further in-depth empirical research in this project.

5.1 INTRODUCTION

Section 2.4.2 in Chapter 2 discussed the idea of processual nature of learning which can be measured and observed in a variety of ways (see section 3.4 in Chapter 3 for example for the specific methods). The processual learning can be examined by gauging learners’ interactions with various learning activities embedded in a course design. Such activities include text-based reading activities (referred to as articles in FutureLearn MOOC designs), instructional videos, assessment activities (like openly accessible quizzes) and discussion-based courses steps.

\textsuperscript{26} Selected findings have been published as:

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Study 2 adopts learning design as a lens for investigating learners’ course activity interaction processes. After assessing the learning processes in a MOOC learning design, the nature and extent of activity engagement for various geo-cultural and socio-economic contexts were explored. The present research reports on our implementation and evaluation of this approach by combining both process-mining techniques with learning design to understand better how and why groups of learners engage in a science MOOC over time.

Learning can be assessed in a variety of ways, ranging from the learning outcomes like grades and certifications (Baker et al., 2016; Wang et al., 2015; Wen & Rosé, 2014), to conceptualising learning as a process (Bogarín et al., 2018; Maldonado-Mahauad et al., 2018). While assuming learning as a process, several studies have recently explored log data to understand learners’ progress, or processual learning, in different MOOC activities (Davis et al., 2016; Guo & Reinecke, 2014; Kizilcec et al., 2013). For instance, to understand learners’ progression in MOOCs, (Kizilcec et al., 2013) used engagement patterns to categorise learners into four categories: completing (completed majority of the assessments), auditing (watched most of the videos but completed assessments infrequently), disengaging (completed assessments at the start of the MOOC, then gradually disengaged). Ferguson & Clow (2015) replicated this method in the context of FutureLearn MOOCs, whereby FutureLearn allows learners to specifically mark activities as ‘complete’. The findings from this replication study suggested that marking few or all activities as ‘completed’ signified a certain level of activity-engagement or learning commitment. Also, such clicking behaviour indicated a strategic way of getting a certificate (Ferguson & Clow, 2015).

Similarly, in a large-scale study of four edX MOOCs (Guo & Reinecke, 2014, p. 6) found that participants exhibited a pattern of ‘non-linear navigation through the course materials’. In particular, it was reported that so-called “certificate-earners” remained inclined towards the application of non-linear navigation strategies, whereby “certificate earners repeated visiting prior sequences three times as often, presumably to review older content.” (Guo & Reinecke, 2014, p. 6). Hence, this research suggested distinct navigational strategies, and that clicking (or not clicking) activities as “completed” represented two distinct psychological dispositions: one when a learner might be inclined to attain a certificate; and the other when learner showed no intention to get a certificate, yet, continued to learn.

Along the same lines, several authors (Davis et al., 2016; Guo & Reinecke, 2014; Wen & Rosé, 2014) have inspected MOOC learning sequences (or learning processes) in connection to assessment results, inclination towards certification, and learning strategies or habits. For example, Wen & Rosé (2014) quarried transitions between two activities and linked the findings with behavioural patterns. A relatively similar approach of using two-step transition to map navigational strategies was used in the work of Guo & Reinecke (2014). Both studies found that generally, learners
progressed linearly, but certificate earners were more inclined to follow unstructured paths. Recently, a slightly different method was used by Davis et al. (2016), who studied MOOC learners’ motivations, like binge (video) watching or ‘quiz checking’ (i.e., checking the quiz answers without attempting the quiz first). To capture the complexities of such motivations, the authors used eight-step long subsets of overall learning sequences. Their findings suggested that learners’ progression through activities and the frequency with which they accessed various learning activities should be seen in the context of their inclination towards certification.

Each MOOC platform follows a distinct course structure and design approach. As discussed in section 2.4.1, a unique feature of FutureLearn MOOCs is that learners can mark a specific learning activity as complete when they (think that they) have sufficiently understood and completed an activity. Given that this research is situated in the FutureLearn environment, it is noteworthy that FutureLearn’s policy on “certificate of participation” allows for non-linear navigation through the activities. In most courses, a learner must mark at least 50% of the course steps as complete and attempt every test question to get a certificate of participation. An initial analysis of log data used in this research pointed towards three distinct clicking patterns, potentially representing three unique dispositions: Markers (i.e., those who marked all their activities as completed); Partial-Markers (i.e., those who marked few of the activities they assessed), and Non-Marker (i.e., those who never marked any of their activities as completed) (Rizvi et al., 2018). This learners’ grouping is unique, and so are the MOOC designs offered via the FutureLearn platform. Nonetheless, this categorisation is informed by similar categorisation stated in previous MOOC literature (Ferguson & Clow, 2015; Kizilcec et al., 2013).

Although several studies have explored MOOC learners’ engagement in various demographic contexts, there is still a paucity of structured research that has explored FutureLearn MOOCs. With enrolments originating from all parts of the world, from all socioeconomic strata, FutureLearn MOOCs are not only diverse but also offer unique learning experience with their distinct LD features (a balance of text reading and video watching activities, essential discussion-based activities etc.). Therefore, for each of the three groups mentioned above, the study first investigates detailed processes of engagement with the learning activities according to an established taxonomy of course activities in the learning design (see section 2.4.1 in Chapter 2). Next, one more layer was added to explore the nature of activity engagement for ten geo-cultural contexts and four socio-economic contexts (see section 3.3.2 in Chapter 3). Overall, the goal of Study 2 is to find empirical support for actionable recommendations to course designers and policymakers who have control over the learning design. The findings of Study 2 can inform context-aware approaches to adapting course content and learning activities, in particular to different groups of learners based on their learning goals as well as their regional backgrounds.
5.2 PURPOSE OF MAIN STUDY AND RESEARCH QUESTIONS

Drawing upon the previous research on understanding learner engagement and progressions through structured learning activities, Study 2 implements and evaluates a two-step approach to understanding learning processes in a FutureLearn science MOOC. The study aims to compare three groups of learners that have been identified in the exploratory phase: Markers (M), Partial Markers (PM), and Non-Markers (NM), whose general behaviour signals distinct inclinations toward certification. Furthermore, for the three group of learners, it evaluates how such behavioural signals vary with geo-cultural and socio-economic contexts. The goal of Study 2 is to uncover similarities and differences in the learning paths and context-based activity engagement behaviours concerning the learning design of the course. Therefore, this research seeks to address the following research questions:

RQ 2.1 How and to what extent does engagement with different learning design elements (i.e., (a) assimilative learning activities (e.g., articles, videos), (b) communication activities (e.g., discussions), and (c) assessment activities (e.g., quizzes)) differ between learners?

RQ 2.2 How and to what extent do temporal learning paths (i.e., sequences of learning activities) differ between learners?

RQ 2.3 How and to what extent does engagement with different learning design elements differ between the geo-cultural contexts?

RQ 2.4 How and to what extent does engagement with different learning design elements differ between the socioeconomic contexts?

5.3 METHODS

5.3.1 Context and Data Pre-processing

The work was conducted after receiving ethical approvals for the project from the OU HREC committee, as well as from FutureLearn. The data was collected from a science MOOC. This large and diverse MOOC was developed by the OU and was offered via FutureLearn in the year 2017. The course enrolled a total of 2086 learners and contained 68 learning activities offered over a span of four weeks. Based on how many activities learners have marked as complete in the course, the study sample was grouped into 449 Markers, 832 Partial-Markers, and 805 Non-Markers. For the purpose of analysis, the following information was extracted from the log files: anonymised learners ID, week number, learning activity-type, learning activity, and timestamps. After the data collection, OULDI framework was employed (see section 2.4) to map the specific activities to general learning design features.
In addition, for the geo-cultural categorization of learners enrolled in the course, the study used GLOBE theoretical framework (House et al., 2004), as described in detail in section 2.5.1. In line with the extensive previous research (Reich & Ruipérez-Valiente, 2019; Kizilcec et al., 2017), the study used IP based locations. Learners’ locations were categorized into ten geo-cultural clusters; Sub-Saharan Africa (AF), Anglo-Saxon (AS), Confucian Asia (CA), Eastern Europe (EE), Germanic Europe (GE), Latin America (LA), Latin Europe (LE), Middle East (ME), Nordic Europe (NE), and Southern Asia (SA). Figure 5.1 illustrates the distribution of learners in ten geo-cultural clusters and also provides a breakdown of the number of learners from each of the three clickstream groups (M, PM, and NM). Furthermore, as described in detail in section 3.3.2, the World Bank classification of world economies into different income categories (World Bank Country and Lending Groups – World Bank Data Help Desk, 2017), learners’ countries were aggregated into four socioeconomic clusters; high income (HI), upper-middle income (UMI), lower middle income (LMI), and lower income (LI). While doing the above categorizations, data was removed for learners whose location was unavailable (n = 60).

![Figure 5.1 Distribution of each group of learners (Markers, Non-Markers and Partial Markers) across ten geo-cultural clusters.](image)

The largest geo-cultural subgroup in the data originated form Anglo-Saxon countries (n = 725, 35.8%) followed by Middle Eastern (n = 328, 16.2%) and South Asian (n = 205, 10.1%) countries. The smallest cluster belonged to the Nordic European region (n = 28, 1.4%). In the largest geo-cultural cluster, the majority of learners (n = 343, 47.3%) were found to be Partial Markers. In contrast, the dominant subgroup in Middle Eastern and South Asian learners never marked any of their activity.
as completed (n = 198, 60.4% in the Middle Eastern cluster and n = 90, 43.9% in the South Asian cluster).

In terms of socioeconomic clustering (Figure 5.2), more than half of the learners belonged to one of the rich and flourishing high income (HI) economies (n = 1,061, 52.4%), whereby most of these learners were grouped as Partial-Markers (n = 477, 44.9%). The second-largest socioeconomic cluster originated from lower middle income (LMI) countries (n = 542, 26.7%). However, almost half of them never marked any of the activity as completed before leaving the course (n = 263, 48.5%). In comparison, the smallest socio-economic cluster originated from countries with lower income (LI) economies (n = 36, 1.8%).

5.3.2 Data Analysis

To understand learning processes in the MOOC and to develop learners’ temporal navigational patterns, Study 2 uses methods typically associated with Educational Process Mining (EPM). For each of the activity types (article, video, discussion, and quiz), the activity engagement differences were first explored in the overall learners’ sample (RQ 2.1 and 2.2), and then separately in all three subgroups of learners (M, PM, and NM) from ten geo-cultural clusters (for RQ 2.3) and four socioeconomic clusters (for RQ 2.4).

5.4 RESULTS

In the exploratory phase of this analysis, the three distinct clicking patterns were found that led to the learners’ categorisation used in Study 2, whereby the following three categories were identified: Markers, Partial-Markers and Non-Markers. The categorisation appeared to be unique
within the relevant FutureLearn context, although this categorisation is partially derived from, and partly based upon, similar categorisation used in previous MOOC engagement literature (Davis et al., 2016; Ferguson & Clow, 2015; Guo & Reinecke, 2014). In terms of hourly activity access, the group of Markers remained far more active throughout the MOOC than Partial and Non-Markers (see Figure 5.3). This was particularly noticeable during the first half of the course, whereas overall activity levels diminished with time for all learners afterwards.

![Graphs showing activity levels for Markers, Partial-Markers, and Non-Markers](image)

**Figure 5.3** Difference of temporal engagement behaviour in all three groups.

From the week one activities, Markers largely accessed some articles (accessed 3876 times), closely followed by discussion (1135), video (804) and quiz (365). However, they typically spent the most time watching videos (median up to 8 minutes 6 seconds) and spent the least time reading an article (median up to 2 minutes 48 seconds). Partial-Markers followed the same pattern. In contrast, Non-Markers preferred watching videos (50% of their overall activities from week 1), followed by article (40.1%), discussion (6.98%), and quiz (2.05%), respectively. However, they often progressed through the course without marking any of the accessed activities as completed. Within week two course content, all three groups remained primarily interested in articles. Although the discussion
was the second most frequent activity, learners started to spend less time participating in a discussion (just more than 1 minute on discussion steps in the case of Markers). In week 3 and 4, Partial- and Non-Markers gradually withdrew from discussions; however, they continued to read articles and viewed videos as before. In comparison, Markers remained mildly interested in participating in the discussion, typically spending less than two minutes on a discussion activity in the last two weeks.

**RQ 2.1 Variation in engagement with elements of the learning design**

In order to analyse variation in learning behaviour across the three groups, and in line with the prior work of Rizvi et al. (2018), Davis et al. (2017), and Liu et al. (2016), the study utilised relative frequency of access for each activity type in relation to the activity distribution in the MOOC. The relative access frequency can represent learners’ interests or a wish to engage with a particular activity type. Furthermore, the relative frequency of access also represents (part of the) general experience of the entire cohort.

Figure 5.4 illustrates the distribution of engagement with course activities for the three groups (raw frequencies are provided in Appendix C, Table C 5.1). It was found that while Markers and Partial-Markers engagement in assimilative and communication activities was equivalent, Markers were more engaged in assessment activities than Partial-Markers. In contrast, Non-Markers were most engaged with a specific assimilative activity, video watching, but less engaged in other assimilative and communication activities: reading articles and participating in the discussion. Non-Markers were also notably less engaged in assessment activities compared to Markers and Partial-Markers. This may be attributed to Non-Markers’ lack of interest in active participation or certification attainment.

Concerning the median time, one can assume that increasing the playback rate can decrease overall time spent on learning from the videos. Still, the short median duration of around two minutes, for example, does not seem enough for article reading. The pattern of short median time for learning activities (like article reading) and long median time for assessment activities (like quiz and test) signifies that Markers and Partial Markers may have spent less time on some learning activities, marked the complete button in haste, and spent relatively more time on assessment activities to get them done correctly.
RQ 2.2 Variation in temporal learning paths and mainstream path identification

In order to address RQ 2.2, the learning paths were mapped based on the clickstream data and then main subgroups within each group were identified. Omitting the self-loop (i.e., repetition) provided more clarity to the process maps. For example, Figure 5.5 shows a simplified view of the learning process model for Markers, filtering out some less frequently occurring paths. Activity access frequency is also denoted alongside each path. A closer inspection of end-to-end learning paths confirmed that although a main pathway existed (dark, thick lines on the map), a large number of Markers preferred non-linear, highly unstructured pathways through the course content. For example, Figure 5.5 shows 22 Markers skipping an assimilative activity (Article: Activity 1.6) to participate in the subsequent activity (Activity 1.7), which was discussion-based. This non-linear

Figure 5.4 Distribution of engagement with course activities as classified by the learning design taxonomy among Markers, Partial-Markers, and Non-Markers. Error bars represent 1 standard error.
progression was consistently noticed in all three groups but, counterintuitively, persisted mainly in Markers.

The study further compared the 15 most common subgroups identified within each of the three primary groups (data available in Appendix C, Table 5.2). These 15 subgroups account for different amounts of the overall activities in each group: 68.6% for Markers, 46.5% for Partial-Markers, and 89.8% for Non-Markers. This distribution shows that there were more variations in the learning processes among Partial-Markers than the other two groups of learners because their overall behaviour was captured less accurately by a small number of subgroups (15 in this case). For each subgroup, the number of activities contained in the learning process was computed. It was found that a third of Markers (31.4%) followed a long learning process containing 67 distinct activities. In contrast, two-thirds of Non-Markers (67.7%) followed a learning process that only contained one activity before they dropped out of the course. In keeping with this pattern, it was found that among the top 15 subgroups, Markers tended to have longer learning processes (6 out of 15 with 50 or more activities), Non-Markers had only short learning processes (11 out of 15 with 5 or fewer activities), and Partial-Markers exhibited a mixture of shorter and longer learning processes (2 out of 15 with 50 or more activities; 4 out of 15 with 5 or fewer activities).

To test the robustness of the observed pattern of variation, a set of $\chi^2$ tests of independence were conducted. The results indicated a significant association between the type of learning activity and whether the learner was a Marker, Partial-Marker or Non-Marker ($\chi^2 = 1279$, df = 8, p < 0.001). It was also confirmed that the lengths of the learning processes were significantly different across the three groups ($\chi^2 = 523$, df = 28, p < 0.001).
Figure 5.5 A simplified view of Markers learning process.
RQ 2.3 LD engagement variation between geo-cultural contexts

The next research question RQ 2.3, examined whether the variations in learning activity engagement differed between geo-cultural contexts. What stands out in the results is that some geo-cultural clusters exhibited activities not aligned with their distribution in the sample. For example, in this science MOOC, the Latin American subgroup comprised more than 14.4% of the overall Markers’ population, but the group was found accountable for more than 17.4% of accessed activities for Markers. On the other hand, South Asian and Middle Eastern clusters comprised over 8.8% and 7.7% of the Markers group, respectively, but each remained responsible for just over 6% of overall Markers’ happenings. Figure 5.6 shows the distribution of activity engagement across ten cultural clusters, first for the entire data and then for each group of Markers, Partial and Non-Markers.

Confirming the results from RQ 2.1 and RQ 2.2, Markers tended to remain aligned with the course activity distribution, signifying minimal cross-cultural differences in activity access frequency. Still, a closer inspection of activity engagement duration suggested otherwise. Within Markers, the second largest and second most active geo-cultural cluster (Latin America) exhibited the smallest median activity duration (median 1 minute 27 sec per session before they marked the activity as completed). In contrast, in other small, less frequent clusters of learners (like from Germanic and Latin Europe), the median activity engagement duration remained just more than 3 minutes per session. In other words, accessing more resources did not guarantee that a geo-cultural group would also spend more time with the accessed resource.
Figure 5.6 An aggregated view of the differences in geo-cultural contexts in terms of the proportion of relative frequency of access for all four types of learning activities (Article, Video, Discussion, Quiz). In clockwise order: (i) Overall behavior; (ii) Markers; (iii) Non-Markers; (iv) Partial-Markers.

The Partial-Markers group appeared to follow the access and engagement-duration patterns of Markers. However, a distinct activity engagement behaviour was noticed within Non-Markers. Within all geo-cultural clusters in Non-Markers, there was an overall increase in assimilative activity access frequency, particularly in video-based activities. Disregarding the small sample of Nordic European Non-Markers (n = 10), the behaviour was most prominent in Latin American and Middle Eastern learners. For these two slightly large geo-cultural clusters, the video-access frequency remained 61.5% and 55.7% of total activities accessed, whereby the course design contained 11.7% videos.
Figure 5.7 Geo-cultural differences in mean frequency of access for four types of learning activities. In clockwise order: (i) Article access; (ii) Discussion access; (iii) Quiz access; (iv) Video access. Error bars represent 1 SE.

Figure 5.7 illustrates the differences between the ten geo-cultural clusters in the average ways they accessed each activity type. Figure C 5.1 to Figure C 5.4 in Appendix C show these differences for each of the subgroups of Markers, Partial-Markers and Non-Markers. Some of the geo-cultural clusters showed consistently more active behaviour (for example, Anglo-Saxon or Latin American clusters). As illustrated in Figure 5.7, some other geo-cultural clusters were slightly less engaged (like African, Middle Eastern, and South Asian learners), where the access frequency fell to the lowest points. Comparing the accessed activities, the extent of disengagement for these less-
interested clustered was particularly distinct in reading and discussion-based activities (i.e., in articles and discussions).

Next, the statistical significance of variation was evaluated for the median activity engagement. Across the geo-cultural contexts, statistically significant differences were found (alpha = 0.05) in all four types of activities (see Table 5.1 for the median activity access). A pairwise comparison (at alpha = 0.05) found that for one activity type or the other, there were differences (all p<0.001) in all pairs except the smallest cluster Nordic Europe (n = 28), which remained unnoticeable.

Table 5.3 Results from the Kruskal-Wallis tests for the activity access behaviour metrics, illustrating activity access differences in geo-cultural contexts. Statistically significant values are in bold. Median activity access is also listed.

<table>
<thead>
<tr>
<th>Measurement metric</th>
<th>Geo-cultural Contexts</th>
<th>AF</th>
<th>AS</th>
<th>CA</th>
<th>EE</th>
<th>GE</th>
<th>LA</th>
<th>LE</th>
<th>ME</th>
<th>NE</th>
<th>SA</th>
<th>H (df)</th>
<th>P</th>
</tr>
</thead>
<tbody>
<tr>
<td>Article access</td>
<td></td>
<td>9</td>
<td>14</td>
<td>9</td>
<td>9</td>
<td>33</td>
<td>10</td>
<td>5</td>
<td>6</td>
<td>8</td>
<td>76.9 (9)</td>
<td>&lt; 0.001</td>
<td></td>
</tr>
<tr>
<td>Video access</td>
<td></td>
<td>1</td>
<td>2</td>
<td>1</td>
<td>1</td>
<td>2</td>
<td>2</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>135.6 (9)</td>
<td>&lt; 0.001</td>
<td></td>
</tr>
<tr>
<td>Discussion access</td>
<td></td>
<td>3</td>
<td>8</td>
<td>3</td>
<td>7</td>
<td>12</td>
<td>7</td>
<td>3</td>
<td>9</td>
<td>3</td>
<td>47.8 (9)</td>
<td>&lt; 0.001</td>
<td></td>
</tr>
<tr>
<td>Quiz access</td>
<td></td>
<td>2</td>
<td>3</td>
<td>2</td>
<td>3</td>
<td>3</td>
<td>3</td>
<td>2</td>
<td>3</td>
<td>2</td>
<td>37.2 (9)</td>
<td>&lt; 0.001</td>
<td></td>
</tr>
</tbody>
</table>

In all three groups of Markers, Partial and Non-Markers, distinct patterns of activity access were found across the cultural clusters (See Figure C 5.1 to Figure C 5.4). Nevertheless, during the pairwise difference analysis, the three smallest subgroups (i.e., Confucian Asia (n = 47), Nordic Europe (n = 28), and Germanic Europe (n = 77)) never surfaced in any of the pairwise differences. Table C 5.3 in Appendix C reports the test results for each of the three groups and the median activity access for all ten geo-cultural contexts.

In terms of article access behaviour, no geo-cultural differences were observed in Markers ($H(9) = 14.62$, $p = 0.10$) or Non-Markers ($H(9) = 10.53$, $p = 0.31$). However, among the Partial-Markers, several differences were noticed ($H(9) = 34.85$, $p < 0.001$). The most unique article access behavioural differences were found between the pairs of Middle Eastern ($Mdn = 6$) versus Anglo-Saxon ($Mdn = 10$) learners and Middle Eastern versus Latin-American learners ($Mdn = 13$). In this MOOC, the video access behaviour across the cultural clusters remained disparate, consistently in all three groups of Markers. Among Markers, the pairs of South Asian ($Mdn = 3$) and Anglo-Saxon ($Mdn = 8$) were found to be most distinct (p < 0.001). Moreover, within Partial Markers, video access behaviour was dissimilar in the pairs of Middle Eastern ($Mdn = 1$) and Anglo-Saxon ($Mdn = 2$) and
Middle Eastern and Latin American ($Mdn = 3$) learners. All in all, for assimilative activities, two distinct patterns of engagement were noticed across the geo-cultural groups, with Anglo-Saxon and Latin American learners on one side (more engaged) and South Asian and Middle Eastern learners on the other side.

The way learners accessed discussion-based activities also varied across cultural contexts, particularly in the groups of Markers and Partial-Markers. For example, for the former, the pairwise difference was prominent ($p = 0.01$) between pairs of Latin American ($Mdn = 12$) versus African ($Mdn = 10$) learners. The quiz access behaviour was different across the geo-cultural context but, unsurprisingly, only for the learners who Marked all activities as completed ($H(9) = 23.14, p < 0.001$). The pairwise analysis suggested the quiz access difference was significant ($p = 0.034$ in both) between Latin American versus African and Latin American versus South Asian learners (however, all $Mdn = 3$).

Overall, it was found that assimilative and communication activity engagement behaviours varied between geo-cultural clusters, mainly among Partial Markers and Non-Markers. However, the median differences in this science MOOC were most prominent in the way learners accessed articles and discussions.

**RQ 2.4 LD engagement variation between socioeconomic contexts**

Using similar approaches to answer RQ 2.4, the study examined the activity engagement differences between four socio-economic contexts. Figure 5.8 illustrates the activity access distribution first for overall data and then for three groups of Markers. As noticed earlier, regardless of the socioeconomic background, Markers and Partial-Markers remained relatively aligned with activity distribution in the MOOC learning design. However, in terms of activity engagement duration, the lowest median duration of 1 minute, 58 sec, was noticed for the Upper Middle-income group. In contrast, the most prolonged engagement duration of 6 min 32 sec was found for the Lower income group.

Most Non-Markers from prosperous High-income economies accessed more reading-based activities (median frequency of article access = 53.7%). While there were 11.7% instructional videos in the course design, learners from Lower Middle-income countries remained interested in watching those videos (median access frequency = 46.1%). Except for Non-Marker learners from high-income countries, overall interest in communication or assessment activities (i.e., discussions and quizzes) remained minimal.
Figure 5.8 An aggregated view of the differences in socioeconomic contexts in terms of proportion of relative frequency of access for all four types of activities (Article, Video, Discussion, Quiz). In clockwise order: (i) Overall behaviour; (ii) Markers; (iii) Non-Markers; (iv) Partial-Markers.
In overall data analysis, statistically significant differences were found in activity access behaviour of all four socioeconomic contexts. As shown in Table 5.2, median activity access is also apparent from Figure 5.9; the most dissimilar pairs (all $P < 0.001$) were Lower or Lower Middle income versus High or Upper Middle-income clusters. Table 5.2 reports the results from Kruskal-Wallis tests to evaluate activity access differences across socioeconomic contexts in overall data. Next, separate
tests were conducted for the groups of Markers, Partial- and Non-Markers (Table C 5.4 in Appendix C).

Table 5.2. Results from the Kruskal-Wallis tests for the activity access behaviour metrics illustrating activity access differences in socioeconomic contexts. Statistically significant values are in bold. Median activity access is also listed.

<table>
<thead>
<tr>
<th>Measurement metric</th>
<th>Socioeconomic Contexts</th>
<th>H (df)</th>
<th>P</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>HI</td>
<td>UMI</td>
<td>LMI</td>
</tr>
<tr>
<td>Article access</td>
<td>11</td>
<td>10</td>
<td>6</td>
</tr>
<tr>
<td>Video access</td>
<td>1.5</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>Discussion access</td>
<td>7</td>
<td>9</td>
<td>3</td>
</tr>
<tr>
<td>Quiz access</td>
<td>3</td>
<td>3</td>
<td>2</td>
</tr>
</tbody>
</table>

While examining the article access differences in Markers ($H(3) = 18.06, P < 0.001$), the pairwise dissimilarities were most significant ($p < 0.001$) in Lower Middle (Mdn = 31) versus High income (Mdn = 44), and Lower Middle versus Upper Middle (Mdn = 44) income groups. Although Markers tended to access more activities than the rest, the variations across socioeconomic contexts were more eminent in Partial Markers ($H(3) = 12.47, P < 0.001$). Once again, article access behaviours of learners from Lower Middle (Mdn = 7) and High (Mdn = 10) income groups remained distinct. In line with the article access behaviour, the video access behaviour was found to be dissimilar in Markers ($H(3) = 20.30, P < 0.001$) where significant pairwise differences ($p < 0.001$) were most noticeable amongst Lower Middle Income (Mdn = 3) versus High/ Upper Middle (both Mdn = 8) income. The differences between Partial or Non-Markers in their video access behaviour remained inconclusive.

In terms of discussion access behaviour, the marginalised Lower-Income and Lower Middle-income contexts remained least engaged (with Mdn = 3 each) and different from Upper Middle (Mdn = 9) and High (Mdn = 7) income groups. But Kruskal-Wallis or follow-up pairwise analysis yielded no useful results except for the Markers ($H(3) = 22.94, P < 0.001$) and Partial-Markers ($H(3) = 12.23, P = 0.007$). Unsurprisingly, the pairwise analysis yielded no differences in quiz access behaviours between High and Upper-Middle income or Lower and Lower Middle income (see Figure C 5.5 to Figure C 5.8 in Appendix C). Overall, in terms of access behaviour for all four activity types, high income and low-income clusters behaviour remained largely dissimilar.

5.5 DISCUSSION AND CONCLUSION

The purpose of Study 2 was to determine the nature and extent of differences in participatory behaviour and temporal learning paths of MOOC learners in relation to the learning activity types.

This investigation aimed to understand the common pathways followed by a substantially large
subgroup of learners (referred to as variants in process mining). While the activity types were attributed from an established learning design taxonomy, the study examined the contrasts in activity engagement behaviour in various geo-cultural and socioeconomic contexts.

An initial exploratory analysis found three distinct clicking patterns. The categorization was based on the degree to which learners marked learning activities they accessed in the course as completed: “Markers” are learners who marked all their activities as completed; “Partial-Markers” are those who marked only a few activities, and “Non-Markers” marked none of their activities as completed. This also reinforces the idea that modifications or alterations in learning designs should be based on the knowledge extracted from the system logs, such as access frequency, duration, transition between activities, the behaviour of clicking the activity as completed and dominant group progression (i.e., relatively large number of learners following the same navigational pattern, accessing the similar activities). The exploratory phase also found regional and other contextual differences in MOOC resource engagement and progression.

The progression trend for individual groups remained aligned with the previous work, as reported in Chapter 4, as well as with other MOOC literature (Ferguson & Clow, 2015; Kizilcec et al., 2013). In contrast to Study 1, Study 2 employed an established learning design taxonomy (as stated in section 2.4 in Chapter 2) to investigate the detailed engagement processes over time. Study 2 identified three primary clusters of engagement (i.e., Markers, Partial-Markers, Non-Markers) in one science MOOC and uncovered similarities and differences in the learning paths of these three groups with respect to the learning design of the course. Notwithstanding the distinct patterns of engagement, the results remained very similar to previous studies in formal online learning setting (Nguyen et al., 2017), showing an overall liking of assimilative activities in general and video-based assimilative activities in particular. Taken together, these results provide insights into learners’ temporal progression or pathways in the MOOC. At the same time, it was noticed that top subgroups (variants) in all groups left the MOOC right after accessing an assimilative activity (either video or article) and rarely after accessing an assessment activity or participating in a discussion.

Furthermore, Study 2 set out to understand how learners from different geo-cultural and socioeconomic contexts engaged with various types of activities and whether there were any meaningful statistical patterns of difference. For this purpose, the activity access frequency and median duration of engagement were used. According to the MOOC data used in Study 2, it can be inferred that the participatory patterns of geo-cultural and socioeconomic clusters remained vastly dissimilar. The differences were generally more prominent for the learners who never marked any of their activity as completed (Non-Markers) and therefore indicated no interest in certification. The findings also suggest that some regions exhibited activities not aligned with their sample
distribution. Some geo-cultural clusters were either overtly active in the course (such as Latin America) while other clusters were less active (like South Asia and the Middle East).

At a fine-grained level, (geo-)cultural background was linked with participation in a number of aspects. For example, while not generally very active in the course, learners from the Middle East and Africa spent the most time on assimilative activities that involved reading an article comprising texts, graphs, and occasional images. In contrast, the Latin American cluster, which was relatively more active than the other geo-cultural clusters, spent the least amount of time on such activities. Both Confucian and Latin American cluster engaged less in communication activities. Middle Eastern, Latin European, and African clusters remained slightly inclined towards assimilative activities of watching videos, and these same groups remained involved only moderately in assessment activities (such as quizzes).

Even though the article access difference among Markers was not statistically significant, the contextual differences were still noticeable. For example, as compared to the rest of the Markers, South Asian and African learners accessed 36% and 14% fewer articles, a result in line with the previous studies that points a general lack of interest in text-based resources among learners from high PD, collectivist regions (Uchiduno et al., 2018; Reinecke & Bernstein, 2013) (Chapter 6 and 7 in this thesis provide a more detailed account of this behavioural pattern). Also, their median video activity access remained as small as three videos and five videos respectively, as compared to median eight videos accessed by Markers from Anglo-Saxon and other European clusters, indicating a disengaged behaviour highlighted by other researchers (Reich & Ruipérez-Valiente, 2019; Kizilcec, Saltarelli, et al., 2017). The pattern remained consistent in the groups of Non-Markers and Partial-markers, where learners residing in English-speaking Anglo-Saxon countries were found to be slightly more inclined towards assimilative and communication-based activities. The median articles and discussion accessed by the Non-Markers from Anglo-Saxon region, for example, was as high as seven, even though not a single article or discussion activity was marked as complete. These findings accentuated an interest in reading content and in taking part in discussions but with no inclination towards certification.

Likewise, varying activity engagement levels were noticed across the four socioeconomic clusters. The two relatively prosperous clusters of High and Upper Middle-income groups remained consistently more active and engaged throughout the course. As indicated by others (Reich & Ruipérez-Valiente, 2019; Kizilcec, et al., 2017), this engagement disparity was found to be consistent in all four activity types in the course learning design. The two less affluent clusters of Lower and Lower-Middle income countries remained disengaged throughout the MOOC offering. Both groups were particularly least interested in discussions (overall median access for a discussion recorded as 3, compared to 7 and 9 respectively for High and Upper-Middle income countries).
Interestingly, the second-largest socioeconomic cluster in the data (26.7%), learners from Lower-Middle income economies, remained least interested in assimilative reading activities. A struggle, as indicated by Nguyen et al. (2020), even when marked all activities as completed (Markers group), these relatively underprivileged learners accessed 29.5% fewer articles than their fellow Markers from High or Upper-Middle income economies. One rather obvious explanation could be that while the internet and access to technology are nearly ubiquitous in prosperous countries, in less developed countries, learners might need to pay to access even lower quality internet connections and other technological resources.

The findings suggest that academics and course designers should give more thought to designing communication and assessment activities for MOOC learning environments to make such activities more appealing to informal learners residing in various regions across the globe. Study 2 suggested that Markers and Partial-Markers access frequencies for all activity types were either aligned with the actual activity distribution or exceeded expectations set by the course learning design. Non-Markers, in contrast, demonstrated massive early dropouts. However, if they continued, they remained substantially interested in assimilative activities of video watching. This result points to Non-Markers’ interest in video-based content, not in textual content (whether assimilative or communicative). Since the activity engagement behaviour differed in all three groups, it can be deduced that if analyses were done without categorising the learners, the results would have remained strongly biased towards the majority class (Partial-Markers in this case). This suggests that while investigating learners’ temporal and engagement behaviour, it is necessary (where possible) to first categorise the learners into natural groups based upon their inclination towards certification.

Taken together, the evidence seems to indicate that the proportion of various learning activity types in a MOOC can have a significant impact on the engagement and persistence of diverse learners. These findings from Study 2, while preliminary, may help us to understand the nature and extent of participation of various cultural clusters in disparate learning activities. The findings raise intriguing questions regarding the nature and extent of participation of various geo-cultural clusters in distinct learning designs, eventually leading to the potential development of a MOOC design that adapts to the cultural needs of prospective learners.

5.6 LINKS WITH OTHER STUDIES IN THIS THESIS

Two research questions (RQ 2.3 and RQ 2.4) in Study 2 were driven from the previous study, Study 1 (Chapter 4), which suggested a predictive link between online learning outcomes and regional belonging. A similar link was found for the poverty level of learners’ region of residence. Convincing evidence from Study 2 indicated that the nature of activity engagement was different for learners who persisted longer. Furthermore, these results laid a foundation for Study 3 (Chapter 6), which
examined ten large MOOCs to understand learners’ persistence in the respective course. Whereby the persistence was operationalized as the percentage of course activities a learner accessed before leaving the course. Study 2 found for example, that engagement with various types of activities varied between geo-cultural and socioeconomic contexts. These findings served as a base for the follow-up study; Study 3 (Chapter 6) explored how a change in the proportion of various activity types (articles, videos, discussions, and quizzes) may predict learners’ persistence in the respective course. Using data from ten MOOCs with ten distinct learning designs, Study 3 further explored how the predictive link varies between geo-cultural and socio-economic contexts.
Chapter 6 Variation in Learning Design and Learners Persistence (Study 3)

As discussed in Chapter 3, this PhD project comprises four connected studies, one building on the other. This chapter discusses Study 3 from the sequence. Study 1 suggested a predictive link between online learners' regional or socioeconomic background and their academic progress (see Chapter 4). The association was found to be dynamic as it varied between various courses with distinct learning designs. Next, Study 2 explored learners' progression and their activity engagement behaviour in a FutureLearn MOOC. The results showed that learners' activity engagement behaviour varied largely between different geo-cultural and socioeconomic contexts. Taken together, the findings from Study 1 and 2 raise a question with considerable practical implications. That is, if we change the proportion of various learning activities in a course, would we notice a change in learners' progression? Also, if the potential association would be dissimilar in different contexts? Therefore, Study 3 empirically examines the link between the variations in learning design elements (four essential learning activity types in FutureLearn MOOC designs: Articles, Videos, Discussion, Quizzes) and learners' persistence. The work further examines the differences across ten geo-cultural and four socioeconomic contexts.

This chapter has been organised in the following way. Section 6.1 introduces the main issues addressed in Study 3. The research questions are discussed in the next part of the chapter (Section 6.2). Section 6.3 is concerned with the methodology employed to answer each of the research questions in this study. The following section (6.4 Results) draws together the key findings, further discussed in the subsequent section (section 6.5, Discussion and Conclusion). Finally, section 6.6 traces the links between Study 3 and three other studies in this PhD research project.

6.1 INTRODUCTION

MOOCs are recognised for their goal of scaling open access to high-quality educational resources. They have been characterised as "courses designed for a large number of participants that can be accessed by anyone anywhere as long as they have an internet connection, are open to everyone without entry qualifications, and offer a full/complete course experience online, for free." (Jansen & Schuwer, 2015). Despite the lofty aspirations of granting people universal access and opportunities for success, prior research has uncovered a range of individual and contextual factors, such as regional, cultural, and socioeconomic backgrounds, that affect individual learning.

The findings from Study 3 have been published as: Rizvi, S., Rienties, B., Rogaten, J., & Kizilcec, R. F. (2021). Beyond One-Size-Fits-All in MOOCs: Variation in Learning Design and Persistence of Learners in Different Geo-cultural and Socioeconomic Contexts. Accepted with minor revisions in Computers in Human Behaviour.
behaviours and outcomes. In particular, recent studies in MOOCs uncovered gaps in learner persistence and performance based on regional and cultural differences (Bozkurt & Aydin, 2018; Ogan et al., 2015) and socioeconomic status (Cai et al., 2017; Kizilcec, Davis, et al., 2017; Kizilcec & Halawa, 2015; Guo & Reinecke, 2014). With an increasing number of people across the globe now learning online, these findings highlight the need to design courses that are accessible and inclusive to all, irrespective of cultural differences.

Most online courses contain various types of learning activities that are delivered uniformly and in a predetermined sequence. In an online learning environment, pedagogical factors, such as the learning design, play a pivotal role in learner engagement, retention and persistence (Mangaroska & Giannakos, 2018; Davis et al., 2018; Rienties et al., 2017; Rienties & Toetenel, 2016; Pimmer et al., 2016; Hernández-Leo et al., 2014). Features of the learning design, such as content type and activity sequencing, can be crucial determinants of persistence. Still, there is limited empirical evidence on the role of learning activities in learners’ course experiences. Moreover, we are limited in our scientific understanding of which learning activity types should be tailored to members of diverse socioeconomic and geo-cultural groups.

Study 3 in this PhD project contributes novel insights into how course learning designs may be adapted for diverse online learners by exploring a heterogenous learner population enrolled in ten large OU MOOCs. This research establishes new links between learner persistence and the types of learning activities they experience in a course. Overall, this work critically empirically examines the premise of one-size-fits-all learning design by simultaneously unpacking the complex interplay between online learning design and learners' cultural and socioeconomic diversity.

6.2 PURPOSE OF MAIN STUDY AND RESEARCH QUESTIONS

6.2.1 Learning designs and learner’s persistence

Several studies on formal online environments (Rienties et al., 2017; Nguyen et al., 2017; Rienties & Toetenel, 2016; Conde & Hernández-García, 2015; Hernández-Leo et al., 2014) and MOOC environments (Rizvi et al., 2020; Xing, 2019) show the critical role of learning design. While learning design can be defined in several ways, a better understanding of the nature of engagement with various learning activity types may lead to ways that we can use to improve persistence. Several other studies have also suggested that learning engagement can be better understood by examining the detailed interactions with various types of learning activities. Such activity types include reading material (Rizvi et al., 2020; Uchidiuno et al., 2018), video content (Davis, 2019; Guo et al., 2014), quizzes (Juhaňák et al., 2017; Li & Baker, 2018), and discussions (Zou et al., 2021; Allon et al., 2016; Sunar et al., 2016; Yang et al., 2013).
As discussed in detail in Chapter 2 (Section 2.4), Study 3 conceptualizes learning design as the process of online course development. A prepared design may have its own advantages. Still, recent literature suggests that a centralised learning design containing a fixed number and types of activities may not necessarily be beneficial for all learners. It can be more useful for some learners while limiting others (Bearman et al., 2020; Margaryan et al., 2015). It is not yet clear whether and how different proportions of these learning design factors enable or restrict learners’ participation.

In line with the approach used in Study 2 (Chapter 5), this study has also taken advantage of an established taxonomy of learning design called OULDI (see section 2.4 in Chapter 2 for more detail). Study 3 focuses explicitly on three OULDI categories representing the principal features in FutureLearn MOOCs: Assimilative activities, Communication-based activities, and Assessments. One rationale behind the activity type selection was that FutureLearn’s MOOC design generally contains the following four types of learning activities: articles, videos, discussions, and quizzes (Sharples, 2015). Each learning activity type has its advantages and limitations. Therefore, the first research question in this study aims to understand if changing the number of various types of learning activities is linked with improved persistence and lower withdrawal from a MOOC.

**RQ 3.1** How and to what extent does the number of learning design elements (i.e., (a) assimilative learning activities (e.g., articles, videos), (b) communication activities (e.g., discussions), and (c) assessment activities (e.g., quizzes)) in a course predict learners’ persistence?

**6.2.2 Learning behaviour and geo-cultural or socioeconomic contexts**

In the context of MOOC learning environments, previous work suggests that there are cross-cultural and regional differences in engagement with various types of learning activities. Comparing several regions or cultural traits, MOOC researchers noticed disproportional assessment or quiz attempts (Liu et al., 2016; Kizilcec & Halawa, 2015), unique video watching behaviour with or without accessing assessments (Z. Liu et al., 2016; Uchidiuno et al., 2018) and social interactions with peers (Z. Liu et al., 2016; Ogan et al., 2015). Relevant literature pointed out that various regions have dissimilar preferences in assimilative activities, with some favouring reading-based materials and others with a fondness for video-based content (Uchidiuno et al., 2018; Z. Liu et al., 2016; Reinecke & Bernstein, 2011). Indeed, settling for a learning design presents a methodological challenge if learners from numerous regions are given manifold choices in learning activities. However, such methodological challenges can easily be addressed with recommender systems and other machine learning methods that perform variable selection to surface essential and relevant feature combinations.

Despite these important advances in knowledge, there is still a paucity of research investigating the overall impact of various learning activity types and their relation to broader geo-cultural
background or socioeconomic status. Also, none of the studies discussed above was conducted using the FutureLearn MOOC platform, which includes explicitly many communication-based activities, which may help or potentially hamper learner engagement from specific regions. This account leads to the next research questions in Study 3, on how the association between learning activity types and learners' persistence in MOOCs is moderated by learners' geo-cultural background (RQ 3.2) and their regions' aggregated income group (RQ 3.3). Study 3 further examines if the strength of the predictive association (from RQ 3.1) differs between geo-cultural and socioeconomic subgroups. In particular, the analysis intends to explore if certain types of learning activities were an enabler for one subgroup but constrained another subgroup, leading to the following key questions:

**RQ 3.2** How and to what extent does the association between learning design elements and learner persistence (from RQ 3.1) differ between geo-cultural contexts?

**RQ 3.3** How and to what extent does the association between learning design elements and learner persistence (from RQ 3.1) differ between socioeconomic contexts?

### 6.3 METHODS

#### 6.3.1 Context and Data Pre-processing

The data set used in Study 3 comprises 49,582 learners from ten MOOCs developed by the OU and offered via the FutureLearn platform. The courses were diverse and vastly dissimilar and were selected based on variability in the learning design factors (types of learning activities) (as shown in Table 6.1). The courses were structured into steps, activities, and weeks. Each week contains several steps comprising various activities. Table 6.1 lists details of four learning design features in each of the ten courses: Articles (A), Discussions (D), Videos (V), Quizzes (Q). The approach used in Study 3 only considers open and freely available assessment activities (i.e., Quizzes) because participants are expected to pay a fee to access formal assessments such as Tests. The sample only included learners with free and limited-time access to the course content. Given the core focus of this research project on open education, Study 3 considered freely accessible activities because the certification fee can be prohibitively expensive for learners in some world regions. These sample exclusion criteria may have introduced selection bias. The criteria were still aligned with the research questions that examine learners' progress through the open and freely accessible course material. Other sporadic miscellaneous learning activities were omitted in Study 3, including exercises, peer reviews, or composite steps consisting of assignment, assignment review, and reflection.
Table 6.1 Number of learners and learners who accessed at least 1% activities (%) in respective courses, median activities accessed (%), and the number of learning design (LD) features (Articles, Discussions, Videos and Quizzes).

<table>
<thead>
<tr>
<th>Disciplines</th>
<th>Course</th>
<th>Learners (n=49582)</th>
<th>Learners with &gt;1% activities (n=34968) (%)</th>
<th>Median activity (%) [LCL, UCL]</th>
<th>A</th>
<th>D</th>
<th>V</th>
<th>Q</th>
</tr>
</thead>
<tbody>
<tr>
<td>Science, Engineering &amp; Math and IT &amp; Computer Science</td>
<td>aml1</td>
<td>1564</td>
<td>1164 (74.4)</td>
<td>8 [6, 8]</td>
<td>32</td>
<td>25</td>
<td>27</td>
<td>24</td>
</tr>
<tr>
<td>Business and Finance Fundamentals</td>
<td>bfec11</td>
<td>6232</td>
<td>3831 (61.5)</td>
<td>9 [7, 9]</td>
<td>40</td>
<td>13</td>
<td>16</td>
<td>5</td>
</tr>
<tr>
<td>Business &amp; Management and Creative Arts &amp; Media</td>
<td>bof7</td>
<td>1819</td>
<td>1264 (69.5)</td>
<td>11 [10, 13]</td>
<td>37</td>
<td>13</td>
<td>39</td>
<td>1</td>
</tr>
<tr>
<td>Nature &amp; Environment and Science, Engineering &amp; Math</td>
<td>ere6</td>
<td>1948</td>
<td>1367 (70.2)</td>
<td>24 [21, 24]</td>
<td>44</td>
<td>12</td>
<td>8</td>
<td>3</td>
</tr>
<tr>
<td>Business &amp; Management</td>
<td>fbg7</td>
<td>1280</td>
<td>689 (53.8)</td>
<td>7 [7, 8]</td>
<td>52</td>
<td>7</td>
<td>24</td>
<td>5</td>
</tr>
<tr>
<td>Business &amp; Management</td>
<td>fpb4</td>
<td>1506</td>
<td>956 (63.5)</td>
<td>12 [10, 15]</td>
<td>44</td>
<td>13</td>
<td>21</td>
<td>3</td>
</tr>
<tr>
<td>IT &amp; Computer Science</td>
<td>ics18</td>
<td>7293</td>
<td>4498 (61.7)</td>
<td>9 [8, 9]</td>
<td>92</td>
<td>23</td>
<td>26</td>
<td>1</td>
</tr>
<tr>
<td>Language and Study Skills</td>
<td>leapfs1</td>
<td>9186</td>
<td>6461 (70.3)</td>
<td>7 [6, 7]</td>
<td>41</td>
<td>16</td>
<td>28</td>
<td>13</td>
</tr>
<tr>
<td>Business &amp; Management</td>
<td>mllt11</td>
<td>4185</td>
<td>3208 (76.7)</td>
<td>8 [7, 8]</td>
<td>60</td>
<td>4</td>
<td>14</td>
<td>4</td>
</tr>
<tr>
<td>Creative Arts &amp; Media and Literature</td>
<td>swf15</td>
<td>14569</td>
<td>11530 (79.1)</td>
<td>8 [7, 8]</td>
<td>78</td>
<td>16</td>
<td>14</td>
<td>6</td>
</tr>
<tr>
<td>Mean ± SD</td>
<td></td>
<td></td>
<td></td>
<td>52.0± 14.2± 21.7± 6.5 ±</td>
<td>19.3</td>
<td>6.3</td>
<td>9.0</td>
<td>7.0</td>
</tr>
</tbody>
</table>
On the FutureLearn platform, the entire content of a course is made available to all learners at the beginning of the course. It remains accessible for a period called "extended enrolment", which is around two weeks. It is recommended that learners engage with the course for 3 to 6 hours per week, watch videos, read course materials, participate in the discussions, and complete quizzes. Since the entire course contents were made available beforehand, the number of learning activities remained constant throughout the course (i.e., time-invariant covariate).

It is important to note here that the learner grouping used in Study 2 did not seem particularly useful in Study 3 (i.e., investigating the link between learning design and persistence with a focus on various contexts) because there were significant variations in the Partial-Markers group. Also, most Partial and Non-Markers accessed only one activity and then became disengaged. That means the number of activities to separately analyse the persistence of subgroups was insufficient. The approach used in Study 3 required an inclusion criterion that ensures to include learners who had accessed enough activities to enable the method to learn something valuable from learners’ progression (this was set as a minimum 1% activities. See Table 6.1). The study did not apply any other inclusion restriction for persistence in a course as that meant implying selection on the dependent variable. Since there is generally no right or wrong in selection criteria, the key, in this case, was finding a balance between the removal of less useful data (those who accessed only 1% of activities) and maintaining diversity. The same inclusion criteria were used for all contexts in order to prevent bias.

Following the procedures used in Study 2 (see Chapter 5), Study 3 also classified learners’ geo-cultural and socioeconomic backgrounds based on their IP address. The GLOBE framework for learners’ geo-cultural categorisation (Chapter 3 section 3.3.2 for more detail) was used to categorised learners' location into ten geo-cultural clusters: Sub-Saharan Africa (AF), Anglo-Saxon (AS), Confucian Asia (CA), Eastern Europe (EE), Germanic Europe (GE), Latin America (LA), Latin Europe (LE), Middle East (ME), Nordic Europe (NE), and South Asia (SA). The distribution over clusters by course is shown in Figure 6.1: the Anglo-Saxon (AS) subgroup made up a consistent majority of the learners in each course (between 15.8% to 57.2%), followed by learners from South Asia (SA), which varied between 10.2% to 31.8%. In comparison, Nordic European (NE) learners were the smallest subgroup comprising only 0.5% to 1.6%.
Next, using the world bank classification of world economies into different income categories (World Bank Country and Lending Groups – World Bank Data Help Desk, 2017), learners’ countries were aggregated into four socioeconomic subgroups; high income (HI), upper-middle income (UMI), lower middle income (LMI), and lower-income (LI). Figure 6.1 illustrates the socioeconomic distribution in the sample. In line with Reich & Ruipérez-Valiente (2019), who indicated disproportionally large enrolment patterns from relatively developed regions, the major stratum (33.6% to 71.4%) in the sample used in Study 3 originated from the flourishing economic subgroup of high income (HI) countries. The second-largest subgroup (17.2% to 47.3%) though belonged to relatively underprivileged countries with lower middle income (LMI) economies.

6.3.2 Measures

Study 3 used learners’ persistence in a MOOC as the outcome measure, assessed based on how far in the course materials a learner progressed before they dropped out. The percentage of activities accessed was calculated to operationalise persistence (% activities accessed). Several predictors or covariate measures were defined to predict the outcome. First, the four learning design predictors were the number of articles, videos, discussions, and quizzes in each course. These covariates contained ten data points, each representing one of the ten MOOCs. The method first used cultural clusters (cc) and socioeconomic clusters (sec) to subset data. Next, these constructs (cc and sec) were used as covariates within the regression equation to measure interactions. Taken together, the following is the list of covariates used in Study 3; (i) Number of learning design (LD) features: Articles (nA), Videos (nV), Discussions (nD), and Quizzes (nQ), (ii) cc: representing ten cultural subgroups, and (iii) sec: representing four socioeconomic subgroups.
6.3.3 Data Analysis

Study 3 used survival analysis methods to measure the effect of the number of different types of learning activities on learner persistence (Labrador et al., 2019; Yang et al., 2013). Instead of a summative measure of success (like certification), Study 3 focuses on learners’ persistence. Prior to the analysis, functional forms of all four learning design features were checked, and satisfactory evidence was found for linear assumptions. Thus, the method used here assumed that the relationship between learning design features and log hazard of early dropout (or hazard to the persistence) were linear in nature. During the survival analysis, the measure of the event of interest represented the respective event of learners leaving the course after accessing a certain fraction of activities. Also indicated in Table 6.1, to perform the survival analysis, the occurrence of an event of interest was defined if a learner accessed at least 1% of course activities and then stopped interacting with the content and left the course (event = 1 when accessed activities >1%, otherwise 0). Table 6.1 lists medians of per cent activity accessed by learners who had accessed at least 1% of activities.

Firstly, the Kaplan-Meier (KM) curves were used to examine the survival probabilities and median survivals. As is common in KM analysis, it was assumed that the survival probabilities remained the same for the learners regardless of their recruitment time, i.e., whether they started early or late. Secondly, complementary log-rank tests were employed to test the differences between survivals. Both methods are non-parametric and make no assumptions about the distribution of the data (see Chapter 3, section 3.4 for more detail). These two methods yield descriptive statistics that address questions such as what proportion of learners will continue learning in their respective MOOCs after a certain point in the course. Next, semi-parametric Cox regression was used for a more nuanced, multivariate analysis (Fox, 2002). Finally, a related machine learning algorithm referred to as Penalised Cox Regression (LASSO_Cox) was used to perform feature selection and simultaneously estimate the regressions coefficient. The methodology chapter in this thesis critically evaluates the rationale behind the methodological approaches used in this project (see Chapter 3 for more detail).

Regularized-Cox allows for various methods. Among other methods (i.e., Ridge-Cox, ElasticNET-Cox etc.), Lasso-Cox has been found to perform better at finding small amounts of signal in data. Therefore Study 3 used Lasso-Cox method (by fitting alpha = 1). During the variable selection, the most regularised cross-validated outcome (Hastie & Qian, 2014), at error within one standard error of the minimum mean cross-validated error (λ.1se), suggested that there were several significant interactions between learning design factors and geo-cultural or socioeconomic subgroups.

The method quantified the impact of the different number of learning activities on the percentage of activities accessed by a learner (RQ 3.1). Following the first analysis for RQ 3.1, it was checked if
the degree of influence was different for the different geo-cultural subgroups (RQ 3.2) and socioeconomic subgroups (RQ 3.3). A large number of two-way interactions between the dimensions of interest (LD*cc, and LD*sec) raised a potential risk of finding spurious relationships. Since the interactions that significantly improve model fitting should be preserved in the model, it was decided to use the regularisation technique of penalised regression. Tables 6.4 and 6.5 in the results section highlight the most critical interactions retrieved from the regularised, ten-fold cross-validated outcome from Penalised Cox regression (Hastie & Qian, 2014).

Table 6.2 Methods employed to address research questions

<table>
<thead>
<tr>
<th>RQ</th>
<th>Methods</th>
<th>Predictors</th>
<th>Results</th>
</tr>
</thead>
<tbody>
<tr>
<td>RQ 3.1</td>
<td>One overarching survival model</td>
<td>nA, nV, nD, nQ</td>
<td>Table 6.3</td>
</tr>
<tr>
<td>RQ 3.2</td>
<td>(i) Subset analysis: Subset data based on the ten geo-cultural clusters (cc) and fit one survival models for each subset.</td>
<td>nA, nV, nD, nQ</td>
<td>Table 6.4</td>
</tr>
<tr>
<td></td>
<td>(ii) Interaction analysis: Fit one survival model to the full dataset and extract important interactions using cross-validation.</td>
<td>cc<em>nA, cc</em>nV, cc<em>nD, cc</em>nQ</td>
<td></td>
</tr>
<tr>
<td>RQ 3.3</td>
<td>(i) Subset analysis: Subset data based on the four socioeconomic clusters (sec) and fit one survival model for each subset.</td>
<td>nA, nV, nD, nQ</td>
<td>Table 6.5</td>
</tr>
<tr>
<td></td>
<td>(ii) Interaction analysis: Fit one survival model to the full dataset and extract important interactions using cross-validation.</td>
<td>sec<em>nA, sec</em>nV, sec<em>nD, sec</em>nQ</td>
<td></td>
</tr>
</tbody>
</table>

The analysis for RQ 3.1 provided overarching results, but at the same time, masked heterogeneity in the diverse sample. Therefore, to answer RQ 3.2, the data were first grouped into ten subsets based upon cultural clusters (cc). Then, subgroup analysis was performed on each of the ten subsets using Cox regression. To address RQ 3.3, the method was repeated on four subgroups for socioeconomic clusters (sec). Developing a separate model for each subgroup enabled the researchers to compare or contrast the findings with the overarching model and across the subgroups. It is essential to highlight here that adopting a separate model for each subgroup assumed the subgroups to be entirely independent of each other. Next, two-way interaction terms were used within the regression equation in order to understand the joint effect of the interacting variables on the persistence hazard profile. This twice-over analysis approach helped to avoid overinterpretation of potentially noisy subgroup results (Lagakos, 2006). The methods for answering each RQ are summarised in Table 6.2.
The FutureLearn MOOC designs comprise numerous small learning steps, each containing several learning activities. The findings suggest that irrespective of the geo-cultural background, a large number of learning activities in a course design was disfavoured by most learners. The following part of this chapter moves on to describe in greater detail the link between each activity type and early dropout risk.

6.4 RESULTS

**RQ 3.1: Association between the number of learning activities and persistence**

Study 3 first confirmed a sufficient degree of variation in the outcome of interest, learners’ persistence, across the ten courses ($\chi^2 = 882, \text{df} = 9, p = < 2e-16$). Next, cox regression was used to evaluate a quantifiable link between persistence and predetermined types of activities in the respective learning design (see Table 6.3). The assumption of proportionality of hazards (PH) was only mildly violated for variable nV ($0.33 > p > 0.02$ in covariate-adjusted Cox regression).

Table 6.3 Coefficient estimates and hazard ratios for the Cox regression model fitted to address RQ 3.1.

<table>
<thead>
<tr>
<th>Predictor</th>
<th>coef (se)</th>
<th>exp (coef)</th>
<th>PH test p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>nA</td>
<td>0.13*** (0.009)</td>
<td>1.14</td>
<td>0.23</td>
</tr>
<tr>
<td>nV</td>
<td>0.03*** (0.007)</td>
<td>1.03</td>
<td>0.02</td>
</tr>
<tr>
<td>nD</td>
<td>-0.03*** (0.008)</td>
<td>0.97</td>
<td>0.33</td>
</tr>
<tr>
<td>nQ</td>
<td>0.14*** (0.007)</td>
<td>1.15</td>
<td>0.10</td>
</tr>
</tbody>
</table>

Significance codes: ‘***’ $p < 0.0001$; ‘**’ $p < 0.001$; ‘*’ $p < 0.01$ ; ‘.’ $p < 0.05$

In Table 6.3, exp(coef) represents the respective hazard ratio for each predictor. Overall, a higher number of learning activities in a course design was associated with an elevated risk of dropout, except for the number of discussion activities. It was found that, while keeping all other activities constant, one unit\(^{28}\) increase in the number of discussion-based activities reduced the dropout risk by 3%. If stated in simple language, an addition of around six more discussion-based activities in a course design that already had about fourteen such activities may potentially decrease the hazard of leaving the course early by 3%.

Likewise, increasing reading activities and quizzes by a unit augmented the risk of dropout by 14% and 15%, respectively. Intuitively speaking, Table 6.1 points to relatively low median activity access for the courses with a slightly higher number of articles and quizzes. A relatively small negative association was found between persistence and the number of videos. For example, if a course already had twenty-two videos, adding nine more videos meant a minimal increase (of 3%) in the hazard of leaving the course early by 3%.

\(^{28}\) The predictors were standardized; therefore, one unit represents 1SD for the respective predictor.
early dropout risk. In other words, a large number of learning activities, particularly articles and quizzes, in a course was associated with an elevated hazard profile. At the same time, this association was reversed for discussion-based activities.

**RQ 3.2: Is the association (from RQ1) different in different geo-cultural subgroups.**

Building on RQ 3.1, it was first confirmed that the survival experiences were dissimilar for different geo-cultural groups ($\chi^2 = 542$, df = 9, $p <= 2e-16$). As shown in Figure 6.2 (and Figure D 6.1 in Appendix D), the Anglo-Saxon subgroup (AS) had the largest presence overall and exhibited the highest median persistence and survival probabilities. In contrast, the second and third largest subgroups, respectively, South Asia (SA) and the Middle East (ME), turned out to be the least persistent throughout. When they reach the 50% activity access mark, both of these subgroups (SA and ME) showed the smallest survival probabilities with 7% and 5% of learners, respectively. Furthermore, only 3% and 2% of learners from these subgroups accessed all activities in the courses (See Figure D 6.1 in Appendix D).

Addressing RQ 3.2, Table 6.4 compares estimated coefficients from (i) subset analysis and (ii) two-way interaction tests, where hazard ratios can be computed by exponentiating these estimates. During the subgroup analysis, the PH assumption was only mildly violated at three points among all 40 points of interaction estimates. A mild violation in PH assumption is common when survival analysis is performed on big data, as the sensitive PH test was originally developed with much smaller datasets in mind. The second column for each activity type reports coefficients from one full model where geo-cultural subgroups interacted with learning design factors. The results from both types of examinations remained primarily identical.
Table 6.4. Comparison of coefficient estimates for the models fitted to address RQ2. The table reports coefficients from (i) subset analysis and (ii) two-way interaction tests. Hazard ratios are computed by exponentiating these estimates.

<table>
<thead>
<tr>
<th>Cc</th>
<th>Learner with &gt;1% activities</th>
<th>Median activity (%)</th>
<th>Articles (A)</th>
<th>Videos (V)</th>
<th>Discussions (D)</th>
<th>Quizzes (Q)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>[0.95LCL,0.95 UCL]</td>
<td>cc subset analysis</td>
<td>Interaction test (cc*nA)</td>
<td>cc subset analysis</td>
<td>Interaction test (cc*nV)</td>
<td>cc subset analysis</td>
</tr>
<tr>
<td></td>
<td>coef (se)</td>
<td>Coef</td>
<td>coef (se)</td>
<td>Coef</td>
<td>coef (se)</td>
<td>Coef</td>
</tr>
<tr>
<td>AF</td>
<td>3391</td>
<td>8 [7, 8]</td>
<td>0.07**</td>
<td>0.07***</td>
<td>0.02</td>
<td>0.09***</td>
</tr>
<tr>
<td></td>
<td>(0.025)</td>
<td>(0.014)</td>
<td>(0.021)</td>
<td>(0.011)</td>
<td>(0.012)</td>
<td>(0.021)</td>
</tr>
<tr>
<td>AS</td>
<td>14839</td>
<td>10 [9, 10]</td>
<td>0.25***</td>
<td>0.24***</td>
<td>0.07***</td>
<td>-0.13***</td>
</tr>
<tr>
<td></td>
<td>(0.035)</td>
<td>(0.011)</td>
<td>(0.038)</td>
<td>(0.026)</td>
<td>(0.012)</td>
<td>(0.043)</td>
</tr>
<tr>
<td>CA</td>
<td>1141</td>
<td>8 [7, 9]</td>
<td>0.14*</td>
<td>0.14</td>
<td>0.06</td>
<td>-0.13**</td>
</tr>
<tr>
<td></td>
<td>(0.054)</td>
<td>(0.054)</td>
<td>(0.038)</td>
<td>(0.026)</td>
<td>(0.043)</td>
<td>(0.040)</td>
</tr>
<tr>
<td>EE</td>
<td>2064</td>
<td>9 [8, 10]</td>
<td>0.06*</td>
<td>0.06</td>
<td>-0.01</td>
<td>0.02</td>
</tr>
<tr>
<td></td>
<td>(0.035)</td>
<td>(0.026)</td>
<td>(0.026)</td>
<td>(0.033)</td>
<td>(0.033)</td>
<td>(0.029)</td>
</tr>
<tr>
<td>GE</td>
<td>1159</td>
<td>9 [8, 10]</td>
<td>0.28***</td>
<td>0.28***</td>
<td>0.03</td>
<td>-0.25***</td>
</tr>
<tr>
<td></td>
<td>(0.052)</td>
<td>(0.037)</td>
<td>(0.037)</td>
<td>(0.045)</td>
<td>(0.045)</td>
<td>(0.040)</td>
</tr>
<tr>
<td>LA</td>
<td>1851</td>
<td>9 [9, 10]</td>
<td>0.39***</td>
<td>0.37***</td>
<td>0.09***</td>
<td>-0.12***</td>
</tr>
<tr>
<td></td>
<td>(0.040)</td>
<td>(0.027)</td>
<td>(0.027)</td>
<td>(0.036)</td>
<td>(0.036)</td>
<td>(0.031)</td>
</tr>
<tr>
<td>LE</td>
<td>1972</td>
<td>10 [9, 10]</td>
<td>0.18***</td>
<td>0.18*</td>
<td>0.08**</td>
<td>-0.11***</td>
</tr>
<tr>
<td></td>
<td>(0.039)</td>
<td>(0.039)</td>
<td>(0.028)</td>
<td>(0.036)</td>
<td>(0.036)</td>
<td>(0.031)</td>
</tr>
<tr>
<td>ME</td>
<td>3039</td>
<td>6 [5, 6]</td>
<td>0.08**</td>
<td>0.08</td>
<td>0.09***</td>
<td>0.10*</td>
</tr>
<tr>
<td></td>
<td>(0.032)</td>
<td>(0.025)</td>
<td>(0.025)</td>
<td>(0.026)</td>
<td>(0.026)</td>
<td>(0.027)</td>
</tr>
<tr>
<td>NE</td>
<td>345</td>
<td>8 [7, 10]</td>
<td>0.19*</td>
<td>0.20</td>
<td>0.04</td>
<td>-0.20*</td>
</tr>
<tr>
<td></td>
<td>(0.095)</td>
<td>(0.068)</td>
<td>(0.068)</td>
<td>(0.081)</td>
<td>(0.081)</td>
<td>(0.075)</td>
</tr>
<tr>
<td>SA</td>
<td>5167</td>
<td>6 [6, 6]</td>
<td>-0.04*</td>
<td>-0.05***</td>
<td>-0.06**</td>
<td>0.19***</td>
</tr>
<tr>
<td></td>
<td>(0.021)</td>
<td>(0.018)</td>
<td>(0.018)</td>
<td>(0.019)</td>
<td>(0.019)</td>
<td>(0.019)</td>
</tr>
<tr>
<td>Cc Learner with &gt;1% activities</td>
<td>Median activity (%)</td>
<td>Articles (A)</td>
<td>Videos (V)</td>
<td>Discussions (D)</td>
<td>Quizzes (Q)</td>
<td></td>
</tr>
<tr>
<td>--------------------------------</td>
<td>---------------------</td>
<td>--------------</td>
<td>------------</td>
<td>----------------</td>
<td>-------------</td>
<td></td>
</tr>
<tr>
<td>[0.95LCL, 0.95 UCL] cc subset analysis</td>
<td>Interaction test (cc*nA)</td>
<td>Interaction test (cc*nV)</td>
<td>Interaction test (cc*nD)</td>
<td>Interaction test (cc*nQ)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>coef (se)</td>
<td>Coef</td>
<td>coef (se)</td>
<td>Coef</td>
<td>coef (se)</td>
<td>Coef</td>
<td></td>
</tr>
</tbody>
</table>

Significance codes: ‘***’ $p < 0.0001$; ‘**’ $p < 0.001$; ‘*’ $p < 0.01$; ‘.’ $p < 0.05$

Entries with light grey font colours were found to be insignificant. Cells highlighted in blue indicate interaction terms that were selected in cross-validation (using cv.glmnet and default lambda = 1se, as recommended (Hastie & Qian, 2014))
The outcomes suggested that keeping all other activities constant, a one-unit increase in articles meant a drastic increase in dropout risk for Latin American (LA) learners (48% increase in risk profile), but a relatively lower increase in risk for Anglo-Saxon (AS) learners (around 28%). In other words, while keeping all other activities constant, adding 19 small reading steps (articles) in a course that already contained 52 readings may potentially result in roughly half of the Latin American learners leaving the course early. This direction of association was the same but less strong for Germanic and Latin European (GE, LE) subgroups, but with no significant cross-validated interaction results.

Surprisingly, the only meaningful interaction between cultural grouping and video-based activities found in the data was for Middle Eastern (ME) learners, where risk increased by 9% for one unit increase in video-based activities, holding other activities constant. Nevertheless, a relatively less critical interaction term (something that did not surface in cross-validated results), increasing the videos, lowered the hazard profile for South Asian learners (by almost 7%). That is how the evidence can be interpreted for an interested layperson; given that the other course activities remain constant, an addition of 9 instructional videos in a course that comprises 22 instructional videos may reduce the early dropout risk for South Asian learners by 7%.

Communication activities have been a critical part of FutureLearn MOOC learning designs. During the analysis, the Discussion-based activities were found to be the most critical activity type, showing an impact essentially different for different geo-cultural clusters. An increase in the number of discussion steps was associated with a reduction in the dropout risk ratio for most learners, except for the learners residing in South Asia and Sub-Saharan Africa. One unit increase in discussions reduced the risk of dropout for Latin American learners by almost 12%. In contrast, it elevated the risk profile by 21% in South Asian learners and nearly 9% in African learners. Alternatively, it was evident that adding six more discussions in course design that already contained fourteen discussions may result in a one-fifth increase in the dropout risk for South Asian learners. Finally, a change in assessment activities (quizzes) deterred most English-Speaking learners (that is, those residing in one of the Anglo-Saxon countries) with an increment of 26% in risk profile.
The subset analysis was most meaningful when it was found that the potential change in the number of learning activities led to precisely the opposite results for the two largest geo-cultural subgroups in data; Anglo-Saxon (AS) and South Asia (SA). Except for discussion steps, the South Asian learners favoured a large number of learning activities overall. Furthermore, mirroring the overarching sample behaviour (as reported in Table 6.3), Anglo-Saxon learners preferred fewer activities overall; more discussion steps kept them engaged. Figure 6.2 illustrates this contrast in learning activity preferences.

RQ 3.3: Is the association (from RQ 3.1) different in different socioeconomic subgroups.

The same modelling steps were repeated for the four socioeconomic subgroups. Figure 6.1 (right) demonstrates the number of learners in each socioeconomic subgroup, and their estimated median activity access in percentages is reported in Table 6.5. The subgroup of learners from high income (HI) countries accessed approximately 3% to 4% more activities before leaving the course than their peers from lower-income (LI) countries. Figure D 6.2 in Appendix D illustrates KM survival curves for the four socioeconomic subgroups. A log-rank test indicated significant differences between survival experiences \( \chi^2=320, \text{df} =3, p =< 2e-16 \). With no overlapping or unparalleled behaviour, each of the socioeconomic subgroups exhibited a distinct course engagement behaviour. The relatively deprived subgroup (lower middle income or LMI) showed the smallest survival probability. Only 7% of learners from that subgroup made it to 50% activity access mark, compared to 13% of those residing in one of the high income (HI) countries. Displaying a consistent parallel pattern, the fraction of these two subgroups fell to 3% and 6%, respectively, towards the end of the course (see Appendix D for more details).
Table 6.5. Comparison of coefficient estimates for the models fitted to address RQ3. The table reports coefficients from (i) subset analysis and (ii) two-way interaction tests. Hazard ratios are computed by exponentiating these estimates.

<table>
<thead>
<tr>
<th>Sec</th>
<th>Learners with &gt;1% activities</th>
<th>Median activity (%)</th>
<th>Articles (A)</th>
<th>Videos (V)</th>
<th>Discussions (D)</th>
<th>Quizzes (Q)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>sec subset analysis</td>
<td>Interaction test</td>
<td>sec subset analysis</td>
<td>Interaction test</td>
<td>sec subset analysis</td>
</tr>
<tr>
<td>HI</td>
<td>20267</td>
<td>9 [9, 10]</td>
<td>0.23 *** (0.01)</td>
<td>0.22 *** (0.009)</td>
<td>0.06 *** (0.01)</td>
<td>-0.13 *** (0.01)</td>
</tr>
<tr>
<td>UMI</td>
<td>5111</td>
<td>7 [7, 8]</td>
<td>0.16 *** (0.02)</td>
<td>0.17* (0.017)</td>
<td>0.04 * (0.017)</td>
<td>0.01 (0.019)</td>
</tr>
<tr>
<td>LMI</td>
<td>8709</td>
<td>6 [6, 6]</td>
<td>0.01 (0.016)</td>
<td>0.01*** (0.014)</td>
<td>-0.01 (0.014)</td>
<td>0.12 *** (0.014)</td>
</tr>
<tr>
<td>LI</td>
<td>881</td>
<td>7 [6, 7]</td>
<td>0.04 (0.05)</td>
<td>0.04 *** (0.05)</td>
<td>0.01 (0.05)</td>
<td>0.09 * (0.04)</td>
</tr>
</tbody>
</table>

Significance codes: ‘***’ $p < 0.0001$; ‘**’ $p < 0.001$; ‘*’ $p < 0.01$ ; ‘.’ $p < 0.05$

Entries with light grey font colours were found to be insignificant. Cells highlighted in blue indicate interaction terms that were selected in cross-validation (using cv.glmnet and default lambda = 1se, as recommended (Hastie & Qian, 2014))
As a result of the cross-validated analysis, no critical interaction was found for the smallest subgroup of learners residing in one of the lower-income (LI) economies. Also, as can be seen from Table 6.5, a large number of learners (more than 36%) from this socioeconomic subgroup dropped out after accessing just one activity, as compared to 25% from the subgroup of learners residing in high income (HI) countries. The high income (HI) subgroup of learners not only accounted for the majority of learners in the sample but also reflected the overall content engagement behaviour noticed while answering RQ 3.1 (Table 6.3). It is important to note here that the high-income group of countries mainly overlapped with the English-speaking Anglo-Saxon, Germanic, or Latin European geo-cultural groups concerning the geo-cultural contexts.

In terms of reading-based assimilative activities, an increase in one unit in the number of articles increased the dropout risk for the high-income subgroup by almost 25% (a pattern noticed in RQ 3.2, see results reported earlier in this chapter). It was a surprise to observe that a change in the number of articles and videos was not significantly linked with the rest of the socioeconomic subgroups, as no active interaction was found after cross-validation.

Learners residing in advanced and wealthy countries preferred more discussion steps in the course (reflecting the behaviour of the Anglo-Saxon geo-cultural group, as discussed previously). The same discussion activity type increased learner's dropout risk for the second largest subgroup of learners residing in one of the lower middle income (LMI) countries by almost 13%. It is essential to highlight here that socioeconomic grouping overlapped with cultural groups. Therefore, many learners from lower middle-income societies were found to be residing in South Asia and Africa.

Finally, learners from the economically affluent high income (HI) and upper middle income (UMI) countries did not favour quizzes. The quiz-based assessment activities did not interact with the other two less prosperous subgroups of learners residing in lower or lower middle income countries.
Consistent with the results from RQ 3.2, the analysis of subgroups yielded contrasting results for the two largest socioeconomic subgroups in the sample. Figure 6.3 illustrates the conflicting behaviour of the two largest socioeconomic subgroups. As mentioned earlier, in terms of geo-cultural grouping, lower middle income socioeconomic subgroup mainly consisted of countries from South Asia, Sub-Saharan Africa, and the Middle East. In other words, learners from wealthy, Anglo-Saxon countries or those from certain European countries were repelled by a large number of articles or quizzes in a course. As for lower middle income (LMI) economies, the only significant cross-validated link for activity change that was observed was for discussions, where a unit increase in discussion activities was found to be linked with a 13% increase in early dropout risk.

6.5 DISCUSSION AND CONCLUSION

Study 3 sets out to find the link between the persistence of 49,582 learners and four learning design factors in ten FutureLearn MOOCs developed in the UK. In the process, the study also examined to what extent the learner persistence probabilities differed between socioeconomic subgroups or between geo-cultural subgroups. The aim of this study was twofold. First, it examined whether a different number of assimilative activities (like articles and videos), communication activities (like discussions), and assessment activities (like quizzes) within a MOOC learning design could be used to predict the overall number of activities learners from across the globe access? Second, the study compared the behavioural differences between ten geo-cultural and four socioeconomic clusters. To address the first research question, it investigated the extent to which the number of various types of learning activities is linked with higher persistence in a MOOC. The second and third research questions measured the variation in these associations in the contexts of geo-cultural and
socioeconomic subgroups. For example, it was found that with the sole exception of learners residing in South Asia, learners overall favoured fewer activities in MOOCs.

Concerning variations in persistence with respect to activity types, the following outcomes were found. Learners engaged heavily in courses with many assimilative activities (articles and videos), specifically those with more videos. Since all the content was made available in the English language, one would expect that Anglo-Saxon learners would be slightly more interested in reading articles. However, a large number of reading-based material in a course was disfavoured by most learners, surprisingly enough, even by learners residing in English speaking countries.

Against the general belief that learning videos should be the central learning feature in MOOC learning designs, the study found an increasing number of videos to be positively linked with the persistence of South Asian learners only. The finding was consistent with previous research (Liu et al., 2016; Reinecke & Bernstein, 2011) that observed a preference for videos or visuals over text, particularly in collectivist countries (such as those from the South Asian region). However, collectively, the growing number of video-based activities was slightly unfavourable to the rest of the regions, both collectivists and individualists, and that regardless of the socioeconomic contexts.

Earlier work suggested that communication-based learning activities are critical for success in an online course (Zou et al., 2021; Rienties & Toetenel, 2016). Still, it was found that they may actually work against learners from disadvantaged, non-English speaking contexts originating from the Global South (lower middle income socioeconomic subgroup and geo-cultural subgroups such as South Asia and Sub-Saharan Africa). In line with others (Liu et al., 2016; Ogan et al., 2015), it was found that the FutureLearn platform’s underlying pedagogy, ‘education in a social learning space’, (Manathunga et al., 2017) worked better for the largest subgroup of western learners, who primarily belonged to English speaking or European countries with affluent economies. However, the same discussion-based activities were found to be constraining countries with limited resources and lower-middle-income levels: South Asian or African regions.

Open discussion of ideas and knowledge is a more common trait in individualistic societies with low power distance scores. This difference in cultural constructs might explain the increased risk profile of South Asian and African learners associated with the number of discussion activities. Previous literature suggests that content in a MOOC can be influenced by the cultural values of the country where the course was produced (Bayeck & Choi, 2018). A FutureLearn MOOC developed in the UK, may probably be designed primarily with UK-based learners in mind (either explicitly or implicitly) while assuming that a large number of discussion-based activities will facilitate learners in general.

Within the MOOC learning environment, learners preferred to be quizzed in moderation. A large number of quizzes led to large early dropouts, specifically for learners from European and Anglo-
Saxon region – mainly upper or upper middle-income countries. In contrast to a previous study (Kizilcec & Halawa, 2015), this study found significant similarities in African and Latin American regions. However, a smaller negative association was found between the number of quizzes and risk to persistence in South Asian and Middle Eastern learners. This might potentially be explained by the fact that most learners from advanced (European or English-speaking) countries may already have high income and education levels (Hansen & Reich, 2015), who would enrol in free online courses for "knowledge attainment" or merely learning for pleasure. Not interested in certification, these learners may be deterred by the increasing number of quizzes in an online course. In comparison, certification might be more important for learners from collectivist, high power distance regions such as South Asia, Africa, and the Middle East. The current study found either negative or a relatively small positive association between the number of quizzes and early dropout risk for these three geo-cultural clusters.

The interaction or subgroup analysis in Study 3 revealed several interesting behavioural patterns. A change in the number of all four types of learning activities led to precisely the opposite results for the two largest geo-cultural subgroups in data: Anglo-Saxon (AS) and South Asian (SA) regions, as well as for the two largest socioeconomic subgroups of high income (HI) and lower middle income (LMI) societies. Overall findings suggest that the result of changing types of learning activities on progress varies mainly with the context.

As discussed in various sections above, the finding clearly demonstrates that an overall analysis of online learning data can mask geo-cultural and socioeconomic heterogeneity in the relationship between learning design and learner outcomes. Consequently, the results of analyses that do not take this heterogeneity into account primarily reflect the behavioural patterns of the largest group, which can stand in contrast to the patterns observed for smaller subgroups. Suppose overall data analysis results are used to guide course design and iterative improvement. In that case, it can result in improved outcomes for the majority group while leaving behind members of underrepresented groups in the course.

While measuring and reporting the subset analysis and term interactions, it was acknowledged that the current study might not have covered all factors linked with learner persistence. The extensive analysis found no perfect recipe for the number of learning activities in any course. There is probably no ideal combination of coherent activities that work for all learners, and Study 3 found the search for inclusive design is a complicated endeavour. In MOOC pedagogy and MOOC learning design, elasticity and flexibility can be recommended. To encourage inclusiveness, the best way forward is perhaps a context-adaptive MOOC learning design. But before we reach the goal of context-adaptive MOOC learning design, this study suggests a balanced approach – a combination of all types of learning activities, not just video-driven, discussion-based, or reading MOOCs.
6.6 LINKS WITH OTHER STUDIES IN THIS THESIS

The research questions in Study 3 were motivated by the findings from Study 2 (Chapter 5) which suggested that learners' engagement with various elements of learning designs (articles, videos, discussions, and quizzes) varied between geo-cultural and socioeconomic contexts. The same study also highlighted a distinct activity engagement behaviour for learners who persisted more in the MOOC. Moreover, Study 1 (Chapter 4) found that the predictive link between online learning outcomes and regional belonging (and socioeconomic status) was dynamic, whose importance changed slightly between various courses with distinct learning designs.

Study 3 employed a sophisticated data mining technique to analyze extensive in-situ log data from ten large MOOCs. Still, it remained unclear how MOOC learners worldwide perceive the role of various elements of learning designs in relation to their engagement in a MOOC. Motivated by this knowledge gap, a follow-up mixed-method study was conducted (see Chapter 7 Study 4). By examining MOOC learners' perspectives about various elements of learning design (different learning activity types and navigation possibilities through those activities), Study 4 seeks to address this research gap.
Chapter 7 Cultural inclusiveness in MOOC learning designs (Study 4)

This chapter discusses Study 4 of this PhD project. Study 4 aims to understand the differences in learners’ perceptions of various learning design elements and how those perceptions vary between geo-cultural contexts. While Study 2 and Study 3 explored learners’ in-situ trace data to understand learners’ navigation (see Chapter 5, findings from Study 2) and their activity engagement behaviour (see Chapter 6, findings from Study 3), both are known to vary between various geo-cultural contexts. It was not clear how learners perceived the role of different learning design elements in maintaining their interest. This mixed-method study uses semi-structured interviews with FutureLearn MOOC learners (n = 22, from seven geo-cultural regions) probing their perceptions about the various elements of MOOC learning designs.

The first section in this chapter (section 7.1) is an introductory section that provides a brief overview of several concepts used in this study, leading to section 7.2, which presents the research questions addressed in this study. The chapter then goes on to the methodology section (section 7.3), which discusses the study design and various mixed methods used for data analysis. The following sections report detailed results (section 7.4) and then a brief discussion of those results (section 7.5).

7.1 INTRODUCTION

As discussed earlier in Chapter 2, massive open online courses are purposefully designed to serve large numbers of learners across the globe, with virtually no restrictions on enrolment as long as learners have access to technical resources required to learn online (Jansen & Schuwer, 2015). A range of studies has found that most learners disengage from the MOOCs at an early stage (Ruipérez-Valiente, Jenner, et al., 2020; Reich & Ruipérez-Valiente, 2019). Quantitative research into online learning environments has suggested a link between course learning design (LD) and learners’ engagement with various learning activities in the course (Rizvi et al., 2020; Nguyen et al., 2017; Rienties & Toetenel, 2016). The degree of engagement with various content types (articles, discussions, quizzes, videos, etc.) varies between regional and geo-cultural contexts (Rizvi et al., 2021; Bearman et al., 2020; Kizilcec et al., 2017; Liu et al., 2016; Ogan et al., 2015). Moreover, several MOOC studies have consistently indicated low persistence rates for learners from non-western regions, particularly from the global South. The cultural diversity represented in course enrolments combined with the continued presence of geographic gaps in learner engagement and

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29 The findings from this chapter have been published as:
achievement raises the question of whether MOOC learning designs are culturally inclusive (enough)?

People's cultural background is known to shape their experience with technology. Previous research on users’ experience with software designs or web-based resources finds that a user’s cultural and regional background influences their perceived enjoyment and perceived usefulness of a given resource (Reinecke & Bernstein, 2013). Both of these experiential factors are strongly correlated with users’ behavioural intention to use that resource (Hornbæk et al., 2017; Davis et al., 1992). The approach used in the current study is similar to that of comparable studies in culturally adaptive user interfaces (Reinecke & Bernstein, 2013; Reinecke & Gajos, 2014), where better perceived usefulness and enjoyment are anticipated to raise resource engagement. Therefore, a culturally adaptive MOOC design may encourage culturally diverse learners and increase participation rates from otherwise marginalised, underrepresented stratum. Recent work on Psychologically Inclusive Design has examined the behavioural consequences of different types of cues (visual, verbal, design, interaction) that can affect learners' feelings of belonging and self-efficacy in an online course based on their social and cultural identity (Kizilcec et al., 2020; Kizilcec & Saltarelli, 2019, 2019). Instead of focusing on content or user interface design cues, this work investigates established dimensions of the course learning design.

The findings from Study 3 support strong predictive links between different learning activities and learners’ persistence (see Chapter 6 in this thesis for more detail). Study 3 analysed learners’ persistence in ten FutureLearn MOOCs, focusing on learning activities deemed essential in FutureLearn MOOC designs. That is, assimilative (such as reading material or articles, instructional videos), communication (such as discussion-based learning activities), and assessment (such as quizzes) activities. It was also found that engagement with these learning activities varied largely between geo-cultural contexts. However, why these differences in engagement were present cannot be determined from quantitative analyses. Therefore, Study 4 in this project aims to understand the rationales behind why learners from particular geo-cultural contexts engage differently with various learning activities within MOOCs. In the process, Study 4 explores learners’ perceived enjoyment and usefulness of various learning design elements in MOOCs using a qualitative approach. It also examines the commonalities and differences between geo-cultural contexts in terms of activity engagement preferences.

7.1.1 Perception of Learning Design and Learning Behaviour

This study conceptualises learning design as an online course development process, where designers design a series of learning activities of different types (audio/video content, reading material, discussion-based activities, and course assessments). Instructional designers arrange these learning activities in a sequence to provide learners with a path to follow. In general, this path
is only indicative and not restrictive, with a course structure that is not static but multimodal with various navigation possibilities (Sharples, 2015). The learning activities can be utilised in several ways, which means that the content can be used repeatedly. However, certain learning activity types may be more useful for some learners, and other learners may perceive them as unimportant or not beneficial (Bearman et al., 2020). Extensive MOOC research has taken advantage of learners’ in-situ trace data to link learners’ persistence with the extent of activity engagement and linearity in navigation patterns (Shi et al., 2020; Davis et al., 2016; Guo & Reinecke, 2014). However, it is not yet known how learners perceive the role of learning design in maintaining their interest in studying. What remains unclear is how learners engage and make sense of the various activity types and whether (or not) the predetermined path benefits their learning.

7.1.2 Learning Behavioural Preferences in Geo-Cultural Contexts

Recent research in learning sciences has found significant global disparities in online course enrolment, engagement and completion whereby the researchers have listed several influencing factors, including learners’ race and ethnicity (Stich & Reeves, 2017; Wladis et al., 2015), geographic location (Reich & Ruipérez-Valiente, 2019; Kizilcec & Halawa, 2015), nature and extent of social integration and help-seeking behaviour (Cagiltay et al., 2020; Ogan et al., 2015), and learners native language (Guo, 2018; Uchidiuno et al., 2018). Driven by previous extensive research, this study draws together four relevant expected behavioural patterns linked with the following elements of learning design: predetermined learning path, discussions, reading material (articles), videos, and assessment activities (see section 2.4 in Chapter 2 for more detail). The role of instructional language has also been explored. As typical in interdisciplinary research, Study 4 draws on multiple theoretical frameworks. The next section describes the theoretical framework for this study.

7.1.3 Theoretical Framework(s)

Considering the differences and extent of coverage of different cultural frameworks and the framework for culturally adaptive user interface design (see section 2.4 in Chapter 2 for more detail), the following approach was chosen to examine the effect of geo-culture on learning behaviour preferences in MOOC learning environment. Figure 7.1 illustrates the key concepts and well-grounded theoretical considerations for this study. This figure also highlights how we tied together various theoretical standards.
**7.2 PURPOSE OF MAIN STUDY AND RESEARCH QUESTIONS**

Several studies (Shi et al., 2020; Rizvi et al., 2020; Davis et al., 2018) have explored the relationship between various learning design elements (learning activity types, the sequence of activities) and MOOC learners’ performance. Later it was also found that this link differs between geo-cultural regions (see Chapter 6 for more detail). Furthermore, most studies in this area have explored the in-situ course log data to understand behavioural engagement patterns, with limited consideration of learners’ perspectives on the various learning design elements. There is still a paucity in research that takes a qualitative approach to explore the broader how and why behind learning design preferences that vary between geo-cultural contexts. In addition to learning design elements, this study aims to assess MOOC learners’ perspectives on the role of English as the primary language of instruction. Therefore, this study poses the following research questions:

**RQ 4.1** What are learners’ perceptions of various learning design elements (i.e., activity types, predetermined path) in relation to their persistence in the course?

**RQ 4.2** In what ways do learners’ perceptions (from RQ 4.1) differ between geo-cultural contexts?

**7.3 METHODS**

**7.3.1 Setting and participants**

Participants for Study 4 were recruited through a social media call using Facebook and Twitter. Participation in the interviews was voluntary, and thus most interviewees were interested in the research topic. All participants had experienced learning from at least one FutureLearn MOOC in the preceding year. Each interview lasted between 30 to 50 minutes. All interviews were conducted via the video meeting platform Zoom and were audio-recorded. After receiving an extensive
response to the interview call (opportunity sample n > 55), diversity and inclusiveness were used as the primary selection criteria. Semi-structured interviews were conducted with 22 participants from seven geo-cultural regions. Following the geo-cultural categorization listed in Chapter 3, five out of seven regions were high PD, collectivist geo-cultural regions. At the same time, two regions were low PD, individualists (see Table E 4.1 in Appendix E for demographic information of the interview participants). The largest number of participants belonged to one of the Anglo-Saxon countries (n = 6/22, 27%), closely followed by South Asian (n=5/22, 23%) and Middle Eastern (n=3/22, 14%) participants. The sample contained no participants from Nordic Europe (NE), Confucian Asian (CA) and Latin Europe (LE). In terms of gender, there was an equal number of male and female participants (n=11/22, 50%). There were slightly more participants with a Masters’ degree (n=13/22, 59%) in the sample.

7.3.2 Procedure and Data Collection Instruments

For each participant, qualitative data were collected using semi-structured interviews. The core interview questions examined the perception of learning activity types and predetermined learning paths (see Table 7.1, for the semi-structured interview guide). Next, to (re)affirm these perceptions, a cultural artifact was used in the final part of the interview (Figure 7.2 illustrates the artifact). The visualisation demonstrated the learning behavioural choices hypothesized for each geo-cultural group (as discussed in section 7.1.2 above and section 2.6 in Chapter 2). The interview questions were retrospective and laid a foundation for further exploration with the help of the cultural artifact. The interviews began with a brief introduction to the host and the project, followed by a set of warm-up questions exploring learners’ motivation for enrollment and overall experience with the course. A set of questions scrutinized the experience with various learning design elements such as predetermined pathway, activity types and instructional language (for a detailed description of the interview process, see Table 7.1).
Table 7.1 Semi-structured interview guide.

<table>
<thead>
<tr>
<th>Introduction</th>
</tr>
</thead>
<tbody>
<tr>
<td>- Self-introduction</td>
</tr>
<tr>
<td>- Project introduction (aims and purpose in brief)</td>
</tr>
<tr>
<td>- Collect consent form and ask for permission to start the recording</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Warm up</th>
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</thead>
<tbody>
<tr>
<td>- Which FutureLearn MOOC did you attend?</td>
</tr>
<tr>
<td>- Why did you attend this MOOC?</td>
</tr>
<tr>
<td>For example, you attended MOOC to complement or achieve the following:</td>
</tr>
<tr>
<td>o Compulsory courses at your institution,</td>
</tr>
<tr>
<td>o elective courses at your institution,</td>
</tr>
<tr>
<td>o continuing education/career development,</td>
</tr>
<tr>
<td>o get a nano degree, vocational/technical/programming training,</td>
</tr>
<tr>
<td>o attain university credit.</td>
</tr>
<tr>
<td>- How do you describe your overall experience with the FutureLearn MOOCs?</td>
</tr>
<tr>
<td>- What was your most favourite part of the course?</td>
</tr>
<tr>
<td>- What was your least favourite part of the course?</td>
</tr>
</tbody>
</table>

1. **Experience with the learning design**

<table>
<thead>
<tr>
<th>Experience with the learning design – predetermined learning pathway</th>
</tr>
</thead>
<tbody>
<tr>
<td>- Do you follow the designed learning pathway, or do you use “to do” list to find activities that interest you?</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Experience with the learning design – learning activity types</th>
</tr>
</thead>
<tbody>
<tr>
<td>- Which of the following activity types in FutureLearn did you enjoy most? Why?</td>
</tr>
<tr>
<td>a. Articles</td>
</tr>
<tr>
<td>b. Videos</td>
</tr>
<tr>
<td>c. Quizzes</td>
</tr>
<tr>
<td>d. Instructor-led Discussion steps</td>
</tr>
<tr>
<td>- Which of the above activity types in FutureLearn did you enjoy least? Why?</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Experience with the learning design – User-led discussions (comments, replies, likes)</th>
</tr>
</thead>
<tbody>
<tr>
<td>- How would you describe your experience with the user-led comments functionality in FutureLearn? Using this functionality, a learner can comment, on any course step, or respond or like other learners’ comments.</td>
</tr>
</tbody>
</table>

2. **Language as a potential barrier?**

<table>
<thead>
<tr>
<th>Language as a potential barrier?</th>
</tr>
</thead>
<tbody>
<tr>
<td>- Did you find language to be a potential barrier, impacting your interest or participation in this MOOC?</td>
</tr>
</tbody>
</table>

3. **For geo-cultural aspects, refer to the Artefact:**

<table>
<thead>
<tr>
<th>For geo-cultural aspects, refer to the Artefact:</th>
</tr>
</thead>
<tbody>
<tr>
<td>- Which of the learner(s)’ views you find more relatable to? Why?</td>
</tr>
</tbody>
</table>
Wrap up and conclude:

- What suggestions or advice would you give to MOOC providers to design or facilitate better MOOCs?
- Is there something we should have asked in this interview that we did not ask? Is there an experience or a feedback you would like to share with us?
- Thank you for your participation

Since distinguishing preferences in a cultural context is a sensitive topic, learning behaviour stereotyping (as discussed in section 2.6 in Chapter 2) must be established subtly. Therefore, instead of asking direct questions (e.g., 'Do you favour video-content over reading material as previous research suggests that learners from your region favour video-based content?' or 'Do you feel comfortable following the predetermined learning path?'), the study utilised a visual mediating artifact in line with recommendations by Mittelmeier et al. (2018). The hypothesized behaviour (that is, learning behavioural preferences, see section 2.6 in Chapter 2) was translated into an artifact (see Figure 7.2). This artifact presented the examples of eight profile learners (Learner 1 to Learner 8), each with a distinct preference for one of the learning behavioural extremes discussed in section 2.6 in Chapter 2. For each profile learner in the visual artifact, the potential originating geo-cultural groups were also mentioned. On a separate page, the information from the artifact was presented in text form with no visuals.

![Figure 7.2 Cultural artifact](image)
The use of a visual artifact offered the interviewer some freedom to explore new dimensions. It provided the interviewee with a way to reaffirm, refute or elaborate on their learning preferences reported earlier. Towards the end of the interview, participants were requested to review the visualisation and then asked to reflect on the information provided in it. Within the eight profile learners’ behaviours depicted in the artifact visualisation, which learners’ profile was more relatable to participants’ own experience in a MOOC learning environment, and why? The visualisation contained complementary information and issues that might have been covered in the main interview questions (e.g., *which learning activity type you enjoyed most?*) but with no mention of participants region of origin. The cultural artifact was discussed in section 3 in the interview guide, while sections 1 and 2 contained the learning design and language-related questions, respectively.

It is worth noting that the artefact mediated semi-structured interview questions are an effective and efficient qualitative data collection method that has widely been used by other researchers (Saldaña, 2015; Bahn & Barratt-Pugh, 2013), particularly in cross-cultural research (Mittelmeier, Rienties, et al., 2018). The method provides a powerful way to encourage a *natural* discussion that can be tailored concurrently to maintain coherence between several discursive contexts, especially when discussing elicit subjects such as geo-cultural learning preferences. The method is particularly useful when participants opt to remain less communicative otherwise and provide a limited verbal response, either reluctant or unable to contribute. One additional rationale for introducing the artefact visualisation was to enable the interviewers to move the conversation forward and assist the non-native English-speaking participant (with limited language fluency) to contribute more on the topic. Interestingly, few minority language speakers in our sample (n > 4) were found to be unfamiliar with the word artifact; therefore, the interviewer used an alternative word, visualisation. Indeed, the artifact contained perhaps stereotypical cross-cultural behaviour. The method supported researchers to channel the discussions into more interesting and informative directions. Even when based on an extensive body of literature, stereotypic assumptions should be made with caution. Therefore, the interviewer used safe and non-intrusive prompts and assertions to engage in an open discussion with the participants. The participants identified their point of view and their concerns and discomfort when exposed to the visualisation. The response has been discussed more in the analysis and results sections. The instruments and procedures used in this study were developed in line with institutional research ethics procedures at the OU (after attaining approval from the OU HREC committee) and in accordance with FutureLearn ethical guidelines and privacy statements.
### 7.3.3 Data Analysis

Interviews were initially transcribed using the transcription tool *otter.ai*. Subsequently, the automated transcriptions were checked manually, and corrections were made where needed. Thematic analysis (TA) was conducted to understand contextual differences in participants’ perception of learning design. By definition, thematic analysis is a qualitative data analysis method used for "identifying, analysing, and reporting patterns (themes) within data" (Braun & Clarke, 2006, p. 6). The method helps make sense of qualitative data by reporting the participants’ experiences and meanings, referred to as the reality of the participants (Braun & Clarke, 2006, p. 9). As discussed earlier in Chapter 3, section 3.4.2, overall, the thematic analysis comprises six-phased processing of interview data to understand the subjective experiences, perceptions and feelings shared by the interviewees (Braun & Clarke, 2006). Another expert and one member of the supervision team repeated the analysis to avoid the risk of subjectivity in the generated codes. The results section in this chapter presents the codes that reached an inter-coder agreement. Section 7.4 below quantifies the results and describes in detail how often the literature-driven expectations were met.

As discussed in detail in section 3.4.2 in Chapter 3, unsupervised sentiment analysis was used to analyse participants’ responses further. Geo-cultural differences in underlying sentiment were recorded and analysed for each of the five activity types (articles, videos, quizzes, instructor-led discussion, and user-led discussion). Sentiment analysis examines the words for positive and negative emotions. The R package *sentimentr* (Rinker, 2017) was used to approximate the sentiment polarity in the transcripts. Regarding the sentiments expressed by the participants, the above listed five activity types were borne in mind. As discussed in the next section, the sentiment scores were then visually compared for all seven geo-cultural contexts in the data.

### 7.4 RESULTS

#### 7.4.1 Learners’ perceptions and cross-cultural differences; Thematic analysis results

As discussed earlier, Study 4 conceptualised learners’ perception of various learning design elements to be linked with their behavioural intention to stay engaged or persist in the MOOC. After clustering the codes under themes, metrics coding analyses were performed to explore the effect of demographic data on their perception of different aspects of MOOC and learning behaviour. All common themes were then scrutinised for any potential link with geo-cultural identities. While examining the perceptions about the MOOC learning environment, several themes were found to be linked with either learning design elements or language or both. Table 7.2 reports the summary and definitions of the codes. The remaining section now discusses the five most frequent and relevant themes that emerged from the thematic analysis.
Table 7.2 Summary and definitions of semi-structured interview codes

<table>
<thead>
<tr>
<th>Code</th>
<th>Number of participants who mentioned code (%)</th>
<th>Sub-Categories</th>
<th>Definition of code</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Structure and Pedagogy</strong></td>
<td>14 (63.6 %)</td>
<td>(a) Interface design and content organisation (b) Workload distribution and content difficulty level</td>
<td>Participants’ perspective on FutureLearn MOOC structure and organisation of learning content, including statements related to the pedagogy, platform interface and overall learning design.</td>
</tr>
<tr>
<td><strong>Interactivity</strong></td>
<td>10 (45.4%)</td>
<td>(a) Interactive communication (instructors’ presence in discussions) (b) Interactive videos (instructors’ presence on screen) (c) Video embedded quizzes (or quizzes immediately followed by videos)</td>
<td>Statements related to the need for improved moderation, including comments and suggestions related to video-interactivity with instructor’s on-screen presence, and video-embedded quizzes.</td>
</tr>
<tr>
<td><strong>Language and Culture</strong></td>
<td>20 (90.9%)</td>
<td>(a) Language barrier in content comprehension (overlapping sub-theme with the theme: Preferential bias) (b) Language barrier in communication (overlapping sub-theme with the theme: Communication) (c) Accent and culture-specific references (including speed, vocabulary, culture/region-specific examples, and jargons) (d) Previous cultural exposure</td>
<td>Participants’ response related to the role of language as a barrier in learning. The code also covers opinion linked to accent, speed, vocabulary, and various jargons used in the MOOC content. Also includes general statements about role of culture and culture-specific references in the visual or textual content.</td>
</tr>
<tr>
<td><strong>Communication</strong></td>
<td>20 (90.9%)</td>
<td>(a) Essential discussion-based activities (that is, instructor-led discussion steps) (overlapping sub-theme with the theme Preferential bias) (b) User-led discussions (c) Lack of privacy/agency</td>
<td>Statements about issues related to communications (Instructor-led and User-led), including a discomfort over lack of agency over one’s own comments, and privacy concerns.</td>
</tr>
</tbody>
</table>
| Preferential Bias | 19 (86.4%) | (a) Preferential bias for activity type (slightly overlapping sub-theme with the theme: Communication)  
(b) Preferential bias for progression | Statements about preferences for learning activity type (i.e., articles, videos, discussions, quizzes). Also includes statements mentioning preferences in linear versus non-linear progression and its link with other factors such as purpose of enrolment, background knowledge, and inclination towards certification. |
i. **Structure and Pedagogy**

One of the most consistent themes that emerged during the interview analysis was related to the structure and pedagogy of FL MOOCs. Fourteen participants described their experiences with the course structure and content organisation. An overall opinion about the weekly workload suggested that the courses fit well within the daily routine without changing it extensively. A few participants expressed their satisfaction with the structure and how they found the course workload manageable. Several participants (e.g., p17) reported their satisfaction with the content’s practicality and balance and the time a learner is expected to spend on the course material.

> It delivered what I wanted it to, and I found it easy to fit in with everything else that I try and get done during the day. (p17, Female, AS)

For example, Participant 7, a learning designer by profession, mentioned her experience with the course structure.

> My most favourite part was structure. It was a well-structured course. It had a standard strict structure. I didn’t feel surprised about anything in the course. There are videos, some text materials and some practice and all the course was like that. (p7, Female, ME)

Participant 15 echoed the opinion by highlighting the clarity in the content presentation and the appropriate combination of various types of learning activities.

> I liked the interface, or the way the course is designed in a way they have these videos for example. So, it’s not just text but there’s a lot of interactive kind of videos … they have this kind of videos to help you with captions to understand what you’re reading and, and some of the different tests, like discussion, all that kind of testing yourself, or the different assignments. (p15, Male, AF)

Overall, the participants thought that the courses were very organised and well-structured. Combining assimilative activities (such as videos and text) with other activities such as discussions and assignments gave the learner a positive learning experience. However, when a participant suffered from a reading disability (or similar), various interesting perspectives were expressed concerning the virtually zero possibility of interface customisation and a lack of flexibility in content layout.

> Maybe more flexible (design)? I don’t think there’s nothing wrong with it. I just really struggle reading from a screen. And so, I’m very sensitive to things like line spacing, line width, font, that kind of thing. So that makes it quite hard for me to read. So, I tune out quite quickly. (p16, Female, GE)
As mentioned in another theme of language and culture, cultural identities surfaced several times. Participants mentioned a broader need to improve diversity in the content and a structure while accommodating the needs of diverse learners.

I've taught a lot of Chinese students, for example, and I think having a really clear structure in place is often very helpful. (p3, Female, AS)

Taken together, we found a small yet clear, identifiable link between participants' geo-cultural identities and their perceptions of course structure, interface, content and organisation. Most participants from High PD, collectivist regions remained satisfied with the easy-to-follow interface of FutureLearn MOOCs, stating the comments like 'feel lost in the course if left without a structure' (p7, Female, ME). In contrast, participants who expressed negative experiences (n = 3) with either the workload, content presentation, or course layout belonged to low PD, individualist regions (AS or GE).

ii. Interactivity

Many participants (~ 45.5%) felt a lack of interactivity in the courses and therefore reported a need for increased interactivity. While acknowledging the associated challenges (e.g., human and technological resources), participants liked to see more presence from the providers in the form of an active instructor, moderator, or facilitator.

When I am learning about something that I don’t know, the learning design should involve also the student support. So, there was no study advisor, no mentor who will answer my questions. (p10, Female, EE)

In another participant’s words,

Make the discussion a little bit more interactive with the people who are actually facilitating the course. But I know that's quite difficult because obviously, the whole point of a MOOC is that it has potentially kind of thousands of participants. Yeah, so maybe something that kind of engages a little bit more with participants throughout the module rather than just kind of the module being placed online. (p3, Female, AS)

Particularly revealing was how participants described their need for improved social interactions using user-tagging or similar social media features in the course discussions to improve engagement.

There was another thing I think should be included more often, and it is for example, participating in the discussion forums. I like using for example, the symbol at (@), like tagging people. So, they know that I'm mentioning them in my in my comment. But it's not that easy to come up with. Sometimes it works,
sometimes it doesn’t. But I think that is a good way to engage other learners in the conversations we are having in the discussion forums. (p1, Female, LA)

As discussed in the communication theme, participants mentioned several features to improve the flow of two-way information, but with more substantial control over their comments. Most of them sought to see the instructors’ existence.

Active live chats! I will comment, and I will engage in a discussion because I would know that there is a person there, reading my comments at that time and liking my comment at that time. And then once the chat is over, my comment is gone. So, there is that control over the comments. So, I have the control I might say, I comment on it, and I know that, I know the reaction. And then once the chat is over, I know that it’s gone. So, I think I would feel more comfortable with that function. (p8, Female, ME)

Interactivity was desired not only in discussion steps but also in the videos. Most participants also favoured interactive quizzes, quizzes embedded in videos or placed right after the instructional videos.

For me, FutureLearn videos do not come as activities because it’s just like information they’re showing... But if they just add the quizzes afterwards, there will be an activity because they’re testing what you heard...starting from a video, then the questions on whatever you are doing. (p1, Female, LA)

The opinion was echoed in other participants’ views.

In the video content itself, there should be some quizzes. That whatever it was, in the teaching, did you get something? I mean based on that there should be a questionnaire. (p2, Male, SA)

This theme consistently surfaced (8 out of 10 occurrences) in the excerpts of participants from high PD, collectivists regions (SA, LA, etc.) who urged more interactivity within various learning design elements. In contrast, participants from low PD only favoured MOOC design features that responded in a synchronous manner to their inputs, either in the form of quizzes embedded in the video or an actively communicating facilitator who answers their queries and appreciates when they share something useful in the discussion forums.

iii. Language and Culture

The data indicated that most participants did not find language an obstacle in the MOOC learning environment. In this respect, we noticed no substantial difference between native and non-native English speakers. MOOC is an open platform with which learners engage on their own accord and according to their interests. However, the learner may not always be a representative of their geo-
cultural region, and it would be reasonable to expect that MOOC learners from the underdeveloped regions in our data may represent a minority, which may not be entirely underserved. Another critical caveat could be sample/response bias. Perhaps the volunteer respondents were individuals who felt comfortable enough to be interviewed in English. Therefore, this theme discussion should be taken with some caution.

Most participants found FutureLearn MOOC language to be relatively easy to follow. However, the language was a potential determining factor in some learning behaviours and implicitly caused preferential bias (see theme 5 below) towards certain learning design elements (such as article reading and social interactions). Occasionally, participants from non-native English-speaking backgrounds indicated their struggle with the learning activities that involved reading textual material. Language barriers were mentioned frequently by non-native English speakers as something negatively influencing their engagement with reading activities. This was cited as,

> When you’re studying (an article) in [participant’s native language], you can pick it quite in a limited time. But when it’s in English, it takes you time to pick up those points and absorb that information. (p6, Male, SA)

As discussed elsewhere, several participants (n > 5) reported that they remained hesitant to participate in MOOC discussion forums because they were not confident about their writing style, grammar, sentence structure, etc. Participants from high PD, collectivist regions stated time and difficulty to express oneself in writing in a second language (English) as a potential barrier for engaging.

> I mean I write my comment, I finish it, and I look at it over and over again, to see whether it is correct or not. So, maybe it’s correct. Maybe it’s like, it’s a perfect comment. But still, I don’t feel that confident, just typing and posting it. So, I have to like, check it again and again before posting. (p8, Female, ME)

Still, none of the non-native English-speaking participants reported difficult words in any of the course activity. The only pertinent concerns noted, if any, were about accent and speed.

> Not the language, okay. Language English I prefer, I am able to understand it. But definitely the tone...the tone, tone quality, you know, the voice was not clear. Whatever he [the instructor] was telling, I was not able to understand. The accent actually! So, that was a language barrier for me. I could see that there are so many people, other people, you know, international people, who liked that course so much. But I didn't like it at all. Okay, so that's definitely, accent can be one barrier for learners like me, or the learner, learners from Asia...See as I am an [participants’ nationality], we prefer the UK English or the US English. But there are some people whose accents we are not able to understand. Okay? Whether he
or she has given a very good content or a very good lecture, okay. But so many times, we
don't understand so we will feel, you know, lack of interest. That if I'm not understanding
anything, I will not put any efforts to whatever is going on. (p2, Male, SA)

However, we observed contrasting opinions about language usage, even within the same region.
More than once, participants mentioned prior language skills and a certain level of digital literacy
as an *informal prerequisite* to the MOOC enrolment.

A small yet clear link was found between participants’ experiences who perceived language as a
learning barrier and their geo-cultural identities. Most participants from high PD, collectivist regions
like the Middle East (2 out of 3) and Africa (1 out of 2) thought that the English language could be
a potential barrier. South Asian learners reported mixed feelings. Several participants from
different contexts raised a need for an internationalised and global perspective, particularly in
instructor-led discussions when they struggled to understand culture/region-specific references
and jargons.

> Sometimes the instructor was giving some examples, which are for mostly for [native] English
speaking people? Like some kind of jokes, and that kind of stuff, maybe movies? He was just
typing that kind of things [in the discussions]. And I couldn't understand at that point, and I
had to go to Google and search for it and understand it. Yeah, it didn't affect my participation,
but I prefer to see more global jokes or more global examples, in the videos especially. (p7,
Female, ME)

Likewise, cultural sensitivity and openness within the platform were also mentioned recurrently.
Others pointed out an interlinked and complex influence of culture and language as a dynamic
factor, which varied with the discussion topic. Overall, we found several links between geo-cultural
identities and issues related to language or culture-specific content. Participants from high PD and
collectivists regions expressed relatively more challenges associated with the language, such as
unfamiliar words and jargon, accent, speed, or culture-specific references in the content and
facilitators’ discussions. Native-English speakers naturally reported no such issues.

**iv. Communication**

Almost all mainstream MOOC providing platforms now allow a social learning space in the form of
either a separate discussion forum or a discussion space right under every learning activity
(FutureLearn design approach) or both. While reading-based activities (i.e., articles) in the MOOC
learning environment were mentioned as the least favourite activity by the largest group of
participants (n = 8), instructor-led discussion activity was mentioned by the second largest group (n
= 6). Some respondents thought discussion activities to be just a reiteration of what they had
already been taught.
Some of them are interesting, but some of them are very repetitive. It is like, can you just now have a discussion forum in one single section please?... sometimes you don't even need to have a discussion forum in MOOCs! (p1, Female, LA)

A large number of ongoing discussions, with numerous discussants participating asynchronously, was an issue for others.

When you don't have time to engage every day, by the time you would log on the discussion, they would already be 20 or 30 posts. (p20, Male, AF)

If discussions were not part of the course steps, most participants thought they would feel a small obligation to participate and could skip it. Several reasons were cited for this. Lack of privacy and control in discussion forums consistently emerged as a reason for disfavour. As the platform does not offer anonymity, learners often hesitate to engage in such an open public forum under their real names. Regardless of their geo-cultural background, only female participants expressed concerns over these issues.

Someone else knowing that I think that way or this way? In the classroom, as I said, I’m okay. I don't need to know these people. I'm okay to share my thoughts face to face, because you say it and it's gone. But in your live platform, your comment stays there. And you can’t really delete it is as far as I know. So that fact makes me uncomfortable. It's beneficial. But to me as a learner, it's not comfortable...Personally, if they weren't compulsory, I wouldn't do them. Because I don't like my comments to be seen by different people and because it's online. (p8, Female, ME)

Consequently, some preferred an increased instructors involvement in the discussions (as mentioned in another theme: Interactivity). Another critical reason cited recurrently was that the MOOC had already been concluded when learners visited the forums. Therefore, they felt like nothing was interesting in the course to keep them engaged. From different cultural contexts, two participants referred to that experience using phrases like 'coming late to the party ...'.

Because the MOOC I mean, it happened in the past. So, it didn't make much sense to discuss now since there were not many people discussing the topic. So, I didn't enjoy this very much. (p19, Male, LA)

In contrast, those who liked communication-based activities thought that instructor-led discussion was an engaging way to trigger interesting debates which contributed towards their learning. Others found them stimulating and confidence-building.

It was important to interact with other students and see if they had some issues, and whether their issues are similar to yours? (p15, Male, AF)
No obvious link was found between the preference of discussions in a course and the geo-cultural identities. It was mentioned as the least enjoyable, *almost unnecessary* activity by most Latin American and South Asian participants. However, the opinion was echoed in other cultural groups as well. If they engaged, Anglo-Saxon participants complained about 'playing catch-up' or 'lack of focus or direction'.

*I read them and I found them really interesting. But I struggled a little bit with seeing kind of what the point was beyond that. Because they were not being moderated.* (p3, Female, AS)

While the instructor-led discussion may eventually evolve to a user-led discussion, such discussions were referred to as 'so much noise made by so many people...' by one of the Anglo-Saxon participants.

*Partly because there were just so many different views and people coming at it in different ways. And it was hard to make any sense of it to kind of find my way among all these hundreds of comments.* (p17, Female, AS)

Some thought the discussion platform was often very unorganised. Additionally, in the absence of a facilitator, the participants were often confused whether the discussion was proceeding in the right direction. But the interviewees who liked user-led discussion took them as an exciting opportunity to advance their understanding of the perspectives from around the globe.

*I think it's pretty interesting knowing about the people that are from around the world. So, you're learning from people. Globally, a diverse group of learners.* (p13, Male, AS)

Regardless of the geo-cultural contexts, several respondents reported user-led discussions to be the least enjoyable and presumably least useful learning activity 30. However, the underlying reasons seemed complex. In contrast with the Anglo-Saxon participants, only a few African, South Asian and Latin American participants found the discussions to be an exciting learning activity. Few participants from South Asia enthusiastically stated that discussions were *'useful and an alternative way to clarify one's concepts.'*

Others mentioned communication activities as time-consuming. Overall, most participants either tended to skip discussions or remained silent observers. Within an open and self-paced MOOC

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30 The overall analysis of quantitative data (see Chapter 6) suggested a rather small, negative association between the number of discussions and persistence in the course (a 3% decrement in dropout risk with 6 more discussion-based steps added in a course already containing 14 discussions). A subgroup analysis suggested that the impact was dissimilar on various geo-cultural subgroups. For example, a negative association between early dropout risk and number of discussions was found for regions such as Anglo-Saxon, Confucian Asia, Nordic Europe, Germanic Europe, Latin Europe and Latin America. As learners from these geo-cultural groups engaged less with the courses containing fewer discussions. While African and South Asian learners in the data did not favour large number of discussion steps in a MOOC learning design (for these two regions, early dropout risk increased by 9% and 23% respectively).
learning environment, discussion participation seemed to be intrinsically motivated. Some participants participated because it was a mandatory activity or part of the course steps/structure. Interestingly, when participants were asked whether they preferred to remain inactive or active in discussions, more people said they would be involved in a user-led conversation at their convenience and pace. However, they still felt irritated by the asynchronous nature of contributions.

*I did not engage as much. People were doing it at different times. It wasn’t that we were all working on it at the same time. And therefore, almost I didn’t care what other people thought to be honest... people had different angles of interest.* (p11, Female, AS)

On the one hand, more participants wished to see more presence of instructors, moderators, or subject matter experts. On the other hand, they felt *unnecessarily* obliged to participate, whereby all learners were permitted to read the content from any ongoing discussions without actively participating. Few benefitted from the information shared by fellow learners without leaving any comments.

*People were sharing (programming) codes and ideas, and they were asking questions about when they were stuck. And like, that was particularly useful once when I couldn’t get something to work. Then I went and had a look to see if anyone else was having trouble. Which saved me from posting...I probably would have liked to look at. I admitted that I was stuck.* (p5, Male, AS)

After introducing the artifact, another interesting dimension emerged related to the discussion group size. The qualitative data showed that more participants from Low PD, collectivist cultural groups were less likely to engage. However, very few of them reported concern about the size of discussion group in MOOCs. Sometimes the respondents provided useful insights into their views on communication and social interaction in MOOCs.

*You might have thousands of people, making a point in front of thousands of people? It is completely different because there’s very little chance that many of them will be listening or paying attention.* (p17, Female, AS)

Among the high PD collectivist participants, several South Asians remained open to contribute more.

*I liked it so much okay. Because let us suppose I learned till 40 minutes or 50 minutes, and now I’m not getting anything. So, I will start a discussion on that point. So, whoever is ready to answer, they will answer, and we'll start discussion that how it is.* (p2, Male, SA)
This theme was slightly overlapping with another theme: Preferential bias. Overall, participants who found discussions useful preferred actively facilitated, synchronous, and live discussions. They also thought they could learn from the forum even after the course/topic has been concluded. The distinction of instructor-led versus user-led in the qualitative analysis supported the idea that European and Anglo-Saxon learners might have actually been looking forward to getting engaged in user-led discussions, starting new posts, replying to the older posts or replying to the replies they had received. Except for some outlier participants, no such inclination was noticed in the other geo-cultural groups. The learners from geo-cultural regions who were interested in discussions were still more inclined towards user-led discussions, and not towards the instructor-led discussion. However, several differences of opinion were found within and across various geo-cultural groups, and the overall analysis remained inconclusive.

v. Preferential bias for learning design

Preferential bias for progression

We noticed a prominent preferential bias for activity navigation patterns. The factors reported to influence participants’ decision to follow (or not to follow) the predetermined path included background knowledge and purpose of enrolment (skill development, certification, personal interest etc.). Most respondents felt comfortable following the designed path. A substantial number of participants thought they would skip steps or slightly go forward if they feel the content was straightforward and had authority on the subject. Few participants said they went directly to the steps they felt interesting and/or necessary.

Out of 9 participants who reported a strong preference for linear progression, six belonged to one of the High PD, collectivists countries. These participants either followed the designed path (mostly) or else their behaviour depended upon the nature of the course, academic background, and purpose of enrolment. Overall, the general belief was that a learner should follow the proposed design for effective learning. All except one South Asian, one Eastern European and one African learner reported a strong or moderate preference for following the predetermined structure.

> Mostly I just try to move according to the designer, or the content developer, like a list of activities they have developed? So, I just like to go the point-wise only, so that I can have a good knowledge for the next topic, accordingly. (p14, Male, SA)

Likewise, other participants from high PD, collectivists regions liked the direction provided by designers as it made more sense and because they trust the instructors or designers. They felt a sense of achievement when they ticked the list of activities as "completed" (a feature in FutureLearn MOOCs).
Because I think it makes (following the design) makes more sense. Someone has actually spent a lot of time thinking about the layout, thinking about the procedure of the learning outcomes. (p21, Female, EE)

This opinion consistently echoed in excerpts of several other participants.

I think when the course is designed by the experts, they design it from the basic to the advanced level, okay? And for example, if we take courses by ourselves, then we would go without attending the basic level we would start advanced learning then that would not make sense for us. So, it’s better to go with the designed course. (p6, Male, SA)

As discussed before (theme: Structure and organisation), the participants reported their liking for the structure provided by course designers.

I like going one by one... otherwise, I feel like I missed something. And I feel like if I skip a few exercises or sessions, I feel like I will find it difficult to complete tasks in the following sessions...it works better for me. I don’t like skipping sessions or skipping, like exercises or something like that. I like going in order if you like. (p8, Female, ME)

Few participants had a unique perspective; for instance, South Asian learners recurrently reported linearity in progression but occasional skipped activities to see only the video content.

I always watch the video lectures. First of all, I always prefer to watch the video lectures. Usually, I do not read articles or go to discussion forums. But I think I follow the list of videos that are recommended by the course (designers). I think I follow the path designed by the instructors instead of (except for) discussion forums and article reading and unnecessary things that are not required to complete the course. Usually, I watch the course videos and directly I jumped to the quiz or exam or graded assignment or things like that. (p4, Male, SA)

Still, we found mixed opinions and differences in point of view on progression preferences, which were dependent upon other factors, as cited by a participant.

Actually, it depends on the course. If it’s a technical course, I prefer to follow the course design. But if it’s a kind of social science or educational science, which I am more familiar with, I prefer to choose my own design. It depends on the topic or it depends on my aim. (p7, Female, ME)

In contrast, most participants from low PD, individualist regions said they did not follow the path and indicated a belief in personal choices. Most Anglo-Saxon and Germanic European participants preferred to pick and choose their own activities of interest and would only follow the design if they were entirely unfamiliar with the subject area.
I don’t do authority so I just kind of skip through it and click through it and just see what picks my interest, read a page and click on or back or randomly...I am definitely someone who finds her own route through things. (p16, Female, GE)

Other participants from low PD, individualist regions echoed the opinion, sometimes moderately.

Splashing around in things that I don’t understand? ... Like, someone has put the effort into take you through a certain way, then it’s probably best to stick with that. Okay! But left to my own devices, I might be a little bit less organised. (p5, Male, AS)

However, many participants mentioned that whether or not they would follow the design path depends on several factors, such as the extent to which they are familiar with the course content, their confidence, and the purpose of enrolment. If they prefer to gain competence, they will choose and pick activities. But if they aim for a certificate, they will likely follow the designed path. Finally, subject area or topic were also mentioned several times,

This is so much topic related. For certain things, having a proper structure might be absolutely what you need to do. For other stuff that might be more philosophical. I mean it might need you to perhaps even start from the bottom sometimes to know when you are going to end up and then revisit. So, it very much depends on the on the topic that you’re learning. (p11, Female, AS)

In terms of following the predetermined sequence of activities in a learning design, ten out of fifteen (~66%) participants from high PD collectivist regions remained aligned with expected behaviour after they were presented with the artefact. That is, those ten participants reported a strong or moderate preference for the learning behaviour exhibited by L1 in the artifact. In contrast, three out of seven (~43%) from low PD individualist regions cited a preference for L2. Overall, the result indicates that the participants from high PD, collectivist regions tend to follow the structure provided by the designers.

**Preferential bias for learning activity type**

This theme reflected participants’ preference for learning activity types (articles, videos, quizzes, instructor-led discussions) and progression through those activities (whether or not they prefer to follow the predetermined path?). Flexibility was offered in the form of a follow-up 'why?' question, which eventually led to this theme. While "keyness" of a theme is not necessarily quantifiable (Braun & Clarke, 2006), this theme naturally had one of the most prominent occurrences, within and across the data items. The sub-theme preferential bias for activity type referred to the instances where a participant mentioned a fondness or disfavour for one particular activity type. The data showed that videos were referred to as the most enjoyable and useful, followed by
articles. Overall, the least enjoyable activity was discussion. Next, this section moves on to discuss the responses for distinct activity type.

a. Videos

Most MOOC learning environments are recognised for their video lecture-based learning designs. Several participants in this study indicated that most instructional videos at FutureLearn MOOC platform were concise yet informative and added value to their learning. Overall, many participants (11 out of 15) from high PD, collectivist regions, favoured short videos.

Most favourite part, I would say the videos. They are really short, like, two minutes or three minutes. But the information is there... So, they're really clear, they give the answer, and they explain stuff in two or three minutes. (p8, Female, ME)

For participants from these regions, the high-quality videos with an on-screen instructor were sometimes perceived to be an excellent alternative to face-to-face learning, and experience a participant referred to as "a virtual classroom" (p14, Male, SA). This is how several non-native English-speaking participants expressed a need for on-screen instructors’ presence.

I needed to see an instructor when I was watching the videos, it was not there. English is not my first language, so I need to see mimics or the face expressions... I just want to see more colourful, more engaging and an instructor... or more than one instructor in the video. (p7, Female, ME)

In contrast, fluent/native English speakers, primarily from the low PD, individualist regions, found such instructional videos to be too slow for their taste. These participants (n = 3) preferred reading the transcripts and elicited the feeling that increasing the video speed only makes them "weird" (p16, Female, GE). This is how the participant reported her experience.

I mean they [videos] are slow because they [the instructors] are always speaking very clearly, and slowly to make sure that you understand. Well, I've now lost my focus and I'm already at some other planet... I hate talking-head videos. They're just too slow for me. You know, in video when you can... all you see is a face or a person doing their talk, but the visuals are not related to what they're saying... That's the type of video just that doesn't work for me, then just give me the text. Give me the script and I'll print it and read it. But what does work for me is when the visuals when the video actually add something. Add something that can't be conveyed in text. (p16, Female, GE)

Other participants from regions such as Anglo-Saxon and Germanic Europe repeatedly reported their disfavour for particular instructional videos in FutureLearn MOOCs.
Moreover, two Middle Eastern participants raised a need for content (academically) richer than short videos. According to the quantitative results (see section 6.4), changing the number of videos was found to have exactly the opposite impact on two largest subgroups in our data (Anglo-Saxon, and South Asian). It was interesting to notice how video-related priorities were distinct in different cultural contexts31. Yet, a combination of video and transcript was often found to be useful. Few participants who did not like videos mentioned reasons like (long) duration, (slow) speed and other technical or aesthetic issues such as low-quality audio/video, instructors’ absence (only low PD, collectivist), colourfulness (or lack of it). The majority of people who liked the video were South Asians (all 5), and Latin Americans (both), followed by Eastern Europeans (two out of three).

While South Asians thought that videos invoked a feeling of real-life classroom experience, Anglo-Saxon participants, when they liked the videos, had different reasons for liking the videos, for example, concision and availability of transcripts (if needed). In contrast, few participants who disfavoured videos thought them to be long. The video’s length was mainly the issue when the videos were not instructional but conversational (interviews, focus groups, etc.) because the content did not require viewers’ engagement beyond a certain level. Whereas slightly slow, clear and easy to follow videos were deemed most useful, engaging learners from the collectivist, non-English speaking learners. Such videos provided them with an experience similar to face-to-face learning. No participant from non-English speaking background said they read transcripts; nonetheless, some would watch videos multiple times to understand the content (n > 2).

b. Articles

Most MOOC learning designs tend to include one or more reading activities, that either contains the reading material or links to other reading resources, or both. Reading-based activities were mentioned as enjoyable by the second largest number of respondents. Articles were deemed to be detailed, rich, engaging, and informative activities that at times provide external links. For some, the video was difficult to focus upon, but articles helped them engage with the topic.

31 During the quantitative data analysis for Study 3 (see chapter 6), minimal significant link was found between changing the number of videos and persistence. However, taking into consideration the presence of ten subgroups, the link was not only quantifiable but also statistically significant for the second largest subgroup in the data (South Asian learners). In other words, every increase of 9 videos in a course reduced the dropout risk for South Asian learners by 6% (given that the course already contained around 22 short instructional videos). In contrast, a slightly negative association was found between the number of videos and persistence of Anglo-Saxon learners, but further analysis found the risk to be not statistically significant. The most significant association was found for Middle Eastern learners (9% increase in dropout risk).
I think I learned much better kind of reading things then kind of watching videos, and I am much more focused doing that. (p3, Female, AS)

The choice of articles as an enjoyable learning activity was not equally distributed throughout the sample. It was found that interviewees with doctoral and/or professional degree favoured articles more than other activities. For instance, 4 out of 6 participants who reported articles to be the most enjoyable activity held a doctoral degree (‘reading-type people’ (p9, Male, ME)). Several geo-cultural groups found text-based learning activities slightly disengaging. In particular learners from South Asia (all except one) and those from Latin America (both) consistently regarded textual content with disfavour, citing them hard to engage with and even boring or unnecessary (it is worth mentioning that these findings echo our quantitative results). Although no specific reasons were given, length of articles, language-related difficulties, and availability of more interesting information through similar (web-based) resources were often mentioned by the participants.

Reflecting the general sentiment of participants from high PD, collectivist regions, a participant suggested that text-based material has no place in MOOCs (p22, Male, SA). Regardless of the geo-cultural belonging, disengagement caused by a disproportionately large number of articles in a course was highlighted by other participants.

I didn’t perceive articles as reading content. And sometimes you can come across quite dense written word or content there. It has to be engaging, because it can be almost like reading a newspaper article. Yeah, quite long in length? I tend to find them to be a little bit, for-information-purpose-only type of thing, and not necessarily engaging. (p13, Male, AS)

The preferential bias was naturally evident after introducing participants to the artifact, i.e., after asking participants to choose between Videos and Articles. Few participants cited that compared to text-based content, they attained equally useful information from videos but in substantially less time. Indeed, a moderate relationship was noticed between the preference for video over text or vice-versa and geo-cultural identities. Interestingly, all South Asian and Latin American participants slightly preferred videos over text. All learners (except two, one with a reading disability) from individualist regions, on the other hand, chose a reasonable combination of both text and video, depending upon the context (discipline etc.).

\[32\] Findings from Study 3 (see chapter 6) reveal that increasing the number of reading activities was associated with an increased risk of dropout (for the dataset used, the analysis suggested an increased dropout risk of 14% for every 20 short reading steps added in a course, if the course already had around 52 such reading steps). The interaction analysis suggested that this dropout risk was most severe and statistically significant for learners from Latin American region (48%) followed by learners from Anglo-Saxon (28%), and African (7%) regions.
Referring to the cultural artifact, while comparing the learning behavioural preference for reading articles versus watching videos, more participants from high PD, collectivist regions (n=11/15; ~73%) were found to align with the expected behaviour (i.e., a strong preference for instructional videos). On the other hand, far fewer participants from low PD individualist regions (3/7; ~43%) cited a fondness for text-based learning activities over instructional videos. The overall trend pointed to a general favour for videos over text, but the choice was more decisive in high PD collectivist societies.

c. Discussions (Instructor-led)

Instructor-led discussions were mentioned by the second largest group of participants and discussed extensively under the theme Communication. Comparing the learning behavioural preferences for discussion participation, more respondents from high PD collectivist regions (9 out of 15 or 60%) were aligned with the expected behaviour (i.e., participate in the course discussions only if mandatory). In comparison, slightly fewer participants from low PD individualist regions (4 out of 7 or 57%) were aligned with the behaviour expected from them (i.e., a strong preference for discussion participation, regardless of the group size). The result suggests general disfavour for discussion-based learning activities amongst all participants, but more so in high PD collectivist regions.

d. Quizzes

Assessment activities are considered an essential part of the learning process, even in flexible, self-paced learning environments like MOOCs. In the qualitative data, a mixed response was noticed about assessment activities (quizzes). Around 9 participants mentioned the quizzes as either most (n = 5) or least (n = 4) enjoyable activity. Participants liked it because it was short and simple, perceived as an interesting tool for self-evaluation. Whereas participants who did not enjoy had several reasons. For example, the activity was meant to test their knowledge, and they did not like to be tested in a self-paced, flexible learning environment. Likewise, learners often did not consider frequent assessments a valuable part of the MOOC learning design.

“I’m not there to be tested on, I would like to, you know, to discover new things.
But I don’t really like to feel that I am tested upon. (p21, Female, EE)

Few of them found quizzes to be too generic or easy to pass (the same reasons cited by other participants for liking the quizzes, deemed a stress-free learning activity). Exploring learners’ perceptions about quiz-based assessment activities revealed various dimensions.

“I like quizzes. I think quizzes can give you a real sense of you know... One, they are fun, and two, it’s good to sort of check. So, I think the quizzes are important. (p12, Female, AS)
As typical in MOOCs, learners do not always access all content and exhibit choose-and-pick behaviour. Therefore, they felt reluctant about being quizzed on course material they might have missed. Regardless of their geo-cultural belonging, the participants remained hesitant about being questioned on the content they tend to skip.

I was looking at [topic name], for example, and a lot of the stuff wasn’t really relevant, so I wanted to skip it. So, being quizzed on it was on wasn’t going to make me learn anymore. (p11, Female, AS)

At the same time, other participants mentioned that they would prefer more challenging and more interactive quizzes. A need for more interactive quizzes or quizzes embedded within the instructional videos was consistently noticed (as discussed briefly in the interactivity theme). In fact, this was the most crucial recommendation that surfaced multiple times during the interviews.

I feel the video plus the quizzes give me the sense of interactivity. So, I’m listening to the lecture and right away right after the lesson I can test my knowledge by answering the quizzes. So, I think they provide more direction. (p19, Male, LA)

No significant link was found between a participant’s geo-cultural background and preference for assessment activities. The only apparent connection was that all participants who raised a need for interactivity in the quizzes belonged to one of the collectivists, high PD regions.

When given an option between competence versus certification, not a single participant from high PD collectivist regions (0%) reported a preference for certification over competence. The response was not entirely unexpected as we never anticipated a respondent to leave such bias on record. Whereas the majority reported a preference for competence and certification both. Surprisingly, only one participant from low PD, individualist region showed rather a unique interest in certification. This is how the participant explained his strong preference for certification over competence.

Can we add to that [host name]? So, the reason why I have to get this certification is because I am in competition with other white learners who are already privileged to have that job without the certificate to prove that they can do it. (Although), in my current role, I’ve got a masters in [the relevant field]. (p13, Male, AS)

In the quantitative research (see Chapter 6) research an increased number of assessment activities (i.e., quizzes) was found to have a negative association with learners’ persistence in the respective course. With the sole exception of South Asian learners, the pattern was common in all geo-cultural subgroups. We found, for example, that adding 7 more quizzes in a course that already had around 7 quizzes, tend to increase the average dropout risk by 15%. As discussed before, this pattern did not mirror the view of the second largest subgroup of South Asian learners, where the association was positive, slightly favouring more quizzes in MOOC learning design. The large, elevated risks we noticed were for learners from Middle Eastern, African and Anglo-Saxon countries (7%, 9% and 21% respectively).
7.4.2 Learners’ perceptions and cross-cultural differences; Sentiment analysis results

The thematic analysis used in this study helped to understand the *meanings* in learners’ self-reported experiences with various learning activity types. A follow-up sentiment analysis was conducted to determine the underlying emotions behind the series of participants’ words.

Irrespective of the geo-cultural context, the overall opinion about instructional videos remained either neutral or positive. However, the median sentiment score was slightly more positive in collectivists’ responses (Mdn = 0.20) than individualists’ responses (Mdn = 0.14). In terms of differences across the contexts, the sentiment score peaked for South Asian participants (see Figure 7.3), which is consistent with the quantitative findings (see section 6.4 in Chapter 6). The sentiment score for videos reached the lowest point at the participant’s response from Germanic Europe, who was consistently critical of the FutureLearn instructional videos. In contrast, participants from high PD, collectivist regions, while conversing about video-related experiences, frequently used words with positive polarities (*like, enjoy, useful* etc.). These participants occasionally supported their narrative with accompanying adverbs (*very, always, too much* etc.), resulting in a peak in video-related sentiments.

Concerning sentiments about article-based learning activities, the scores declined to negative for Latin American and South Asian participants’ comments. In line with the qualitative findings (see section 6.4 in Chapter 6), the median sentiment score remained positive for individualists (Mdn = 0.18) but slightly negative for collectivist participants (Mdn = -0.01). The decline in sentiment scores for South Asian and Latin American participants seemed to be caused by the comments containing large negative polarities (*useless, boring, difficult* etc.).

Guided by the previous literature, it was originally anticipated that participants from high PD contexts would be more disinclined toward discussion participation. But sentiment analysis yielded different results with low PD slightly negative in both instructor-led (Mdn = -0.14) and user-led (Mdn = -0.1) discussions. High PD participants however, reported more positive opinions about user-led discussions (Mdn = 0.13) as compared to instructor-led discussion (Mdn = 0.06). Interestingly, this quantification supported thematic analysis results (see theme *Communication*).

Overall, participants from all geo-cultural contexts remained unenthusiastic about instructor-led discussion steps in a course but occasionally reported a willingness to participate in user-led discussions. In the qualitative data, low PD, individualist participants’ comments contained words with large negative polarities (*noise, hard to make sense* etc.). In addition, several participants from low PD, individualist regions questioned large number of discussion activities in a course (*‘You are supposed to be on your own in a MOOC, so why (there are) discussion steps?’* p12, Female, AS).
Although qualitative data analysis revealed no link between geo-cultural identities and participants’ perceptions about the quizzes, the overall sentiment score was found to be positive for collectivists (Mdn = 0.20) but slightly negative for individualists (Mdn = -0.10). The participants from high PD collectivist regions exhibited limited enthusiasm but an overall positive sentiment for quiz-based activities. With large variations in opinions and a great number of outliers, the sentiment analysis for quiz related comments remained inconclusive. Figure 7.3 (a) to (e) illustrate the contextual differences in sentiment scores.
Figure 7.3 (c)

Discussions (user-led)

- Sentiment Score
- Geo-cultural Groups

Figure 7.3 (d)

Quizzes

- Sentiment Score
- Geo-cultural Groups

Figure 7.3 (e)
7.5 DISCUSSION AND CONCLUSION

Study 4 set out to explore learners’ perceptions of various learning design elements in MOOCs and the extent to which these perceptions vary between geo-cultural contexts. While a large number of empirical studies (Bearman et al., 2020; Kizilcec et al., 2017; Liu et al., 2016; Ogan et al., 2015) found that learners from different parts of the globe engage substantially differently in MOOCs, both in terms of the learning process as well as in learning outcomes. Still, there remain questions about the sources of such variations in engagement. Qualitative research can provide useful evidence to address those questions and explain why these differences might occur. Findings from this semi-structured interview-based study revealed learners’ perceptions and the reasons behind those. As the interview response alone may not always convey the whole experience, a visual artifact was also used that voiced the distinct behavioural preferences in different cultural contexts.

Since most early MOOCs were offered in mainly a video-lecture format, instructional videos have long been assumed to be a central feature in a MOOC learning design. Assimilative activities that involved watching videos were considered most enjoyable by most participants. This finding points out the critical role of many instructional videos in maintaining learners’ engagement in MOOCs. A generally strong preference for the video was most dominant in responses of non-English speaking participants from high PD, collectivist regions such as South Asia, followed by Latin America. The result aligns well with the findings from Study 3 (See Chapter 6, section 6.4) that suggested an association between a large number of videos and low drop-out risk for learners from high PD collectivist regions (such as South Asia). Still, in line with the previous work (Uchidiuno et al., 2018), several participants from these regions mentioned issues that may cause disinterest in instructional videos. The issues included (long) duration, speed, instructors’ accent, and low-quality visuals in instructional videos. Standing in exact contrast, participants from low PD, primarily individualist regions, reported disfavour for clear instructional videos from FutureLearn MOOCs, deeming them too slow and slightly disengaging.

As all the content in all MOOCs participants were enrolled in was offered in English, an article favouring behaviour was expected from native English-speaking learners from Anglo-Saxon and European regions. The analysis suggested that reading-based assimilative activities (articles) were considered least enjoyable by a large number of participants, especially by most non-native or less fluent English speakers from high PD, collectivist regions, as they reported to struggle with these activities. The result was in line with (Uchidiuno et al., 2018) that found non-native English speaking learners to engage least with narration (in the videos) that has no visual supports. While Middle Eastern participants reported a desire to learn from either vibrant videos or something richer than videos (i.e., detailed, informative articles). Sentiment analysis results also partly confirm the results.
from thematic analysis and from Study 3 (see Chapter 6 section 6.4) that suggest that non-native or less fluent learners from regions such as South Asia and Latin America find it difficult to engage with text-based activities. It could be due to a need to spend more time with reading-based activities (Nguyen et al., 2020) or pausing videos presenting textual information (lecture summary) (Uchidiuno et al., 2018).

Contrary to expectations set by extensive previous work (Liu et al., 2016; Ogan et al., 2015; Hofstede, 1986), more participants from low PD, individualist regions remained reluctant to engage in communication activities that were part of the course design (instructor-led discussions). In contrast with previous work that pointed toward the critical role of discussions in MOOC learning (Manathunga et al., 2017; Allon et al., 2016), Study 3 (Chapter 6) found that learning designs which provided many opportunities to interact with the peers by instructing learners to discuss certain course topics, actually averted active participation of learners from non-English speaking geocultural regions, such as Sub-Saharan Africa and South Asia. However, the sentiment score was found to be overall positive for high PD.

These findings, however, do not stand in contrast with the research conducted to examine intercultural differences in emotional expressivity and reported that collectivists do not disregard the whole spectrum of emotional expression. Still, they prefer socially engaging emotions (liking, favour) over socially disengaging emotions (disappointment, anger) (Stein & Ohler, 2018). Stein & Ohler, (2018) for example, recently argued that sociocultural factors offer a clear potential to determine which part of the subjective experience is presented to the environment. Perhaps for these reasons, the collectivist participants avoided using words with large negative polarities when expressing opinions about communication activities in a course design. Therefore, the finding that there were relatively fewer negative aspects reported by specific cultures does not necessarily mean that these participants did not experience any negatives. The result also remained somewhat in contrast with the quantitative results from Study 3, which found that many discussion activities in a course design only slightly supported learners from Anglo-Saxon and European regions.

The findings indicated several distinct behavioural preferences that varied between various geocultures. The primary purpose of MOOC enrolment was also diverse. Several participants liked to engage with simple assessment activities i.e., quizzes (cited as fun multiple times). They reported gaining competency, informal continuous professional development (CPD), or following their interest as enrolment purposes. Most participants from low PD, individualist regions said that they enrolled to gain competency (or CPD) or follow their curiosity. Concerning the assessment activities in MOOCs, Study 3 (see Chapter 6 section 6.4) found learners to persist more in the courses that offered fewer quizzes. At the same time, learners from English speaking and European regions liked to be quizzed in moderation. Participants from other regions (like South Asia and Latin America)
said they valued both certificate and competency but reported no particular interest in quiz based activities. Previous work (Liu et al., 2016; Kizilcec & Halawa, 2015) has also found learners from these regions to be comparatively less persistent in taking part in MOOC assessments. Participants worldwide consistently raised a need for more interactive quizzes or quizzes or embedded in the videos.

In line with previous research (Reinecke & Gajos, 2014; Reinecke & Bernstein, 2013; Hofstede, 1986), more participants from high PD, collectivist regions reported following the designed paths in MOOCs. Regardless of their geo-cultural identity, a large number of participants reported the English language as not a substantial barrier to learning in a MOOC learning environment. However, it was said to potentially restrict non-English speakers’ engagement in course discussions. The most frequent and unanimous recommendation arose from high PD, collectivist participants, that is, the need for instructors’ presence in more activities, particularly in user-led discussions. The consulted literature provided us with a reasonable assumption of how the participants might differ in their reactions. The literature points out that high PD, collectivist learners might need more external regulations and a consistent confirmation by the instructor, reflecting a cultural tendency to value interdependence. The individualist, low PD learners, might be more inclined to work by themselves, towards personal goals, and with limited support from the individual in power (instructors and moderators in this case). The overall findings from this study should be taken with caution as the preferences for learning design elements do not necessarily correlate with the learning outcomes for example.

A large number of MOOCs have been predominantly developed by individualistic countries with low power distance (Jadin & Gaisch, 2014). This may have remained unnoticed previously, but extensive literature investigating contextual differences in MOOC engagement now increasingly indicates the need for overall diversity and that specific requirement of different societies should be taken into consideration.
Chapter 8 General Conclusion and Discussion

This final chapter in this thesis now aims to provide general conclusions and discussions about each research question. The first section (8.1) reintroduces the overarching goal of this research. The following section (8.2) describes the novel contributions to knowledge to which this research has contributed. The following section (8.3) summarises the methodological contributions of this research. Section 8.4 outlines the overarching limitations attached to this research and suggests considerations for related future research by identifying interesting areas that need further exploration. Section 8.5 discusses how the research has provided actionable insights that have implications for practice. Finally, section 8.6 concludes the chapter.

8.1 INTRODUCTION

Recent years have observed a shift in the global education landscape. The growth in various modes of online or hybrid learning environments has opened a door of opportunities to learners worldwide. Given an advancement in scalable online learning technologies, coupled with a rising number of open online enrolments from all around the world, MOOC learning environments offer a clear potential to address the global disparity in education. Based on an extensive body of cross-cultural research in the online learning domain, this thesis has argued that learners’ contexts can be particularly relevant to understanding how learners engage with online courses (see Chapter 2). Section 2.2 in this thesis has also cited previous work suggesting that learners’ geo-cultural contexts might potentially shape distinct preferences for the various elements of a course learning design (LD). Since any alteration or modification in course LD should not be done without taking into consideration various pedagogic details, conceptualising a LD that adapts to the needs of learners from different contexts could be quite challenging.

This thesis was built upon this background to unpack the potential role of learners’ contexts in successful online learning. In doing so, the thesis has addressed the engagement behavioural differences in relation to pedagogical contexts (such as LD). To provide valuable, actionable insights, the thesis examined the association between various elements of learning designs and learners’ persistence and then explored how this association varies across learners geo-cultural and socioeconomic contexts. Finally, the thesis examined the potential underlying reasons for the contextual differences and tried to understand ‘why’ learners’ LD preferences may have differed across the contexts?

34 This research conceptualises course learning design (LD) as the outcome of a process of online course development where the designers create various pedagogical constructs such as a series of learner-facing learning and assessment activities (e.g., reading activities, instructional videos, quizzes).
In the process, the thesis has addressed the following research questions:

**RQ 1.1** To what extent is there an association between learners' demographic characteristics (i.e., Regional context, Socioeconomic context, Education, Age, Gender, and Disability) and online learning outcomes throughout the online course?

**RQ 1.2** To what extent does the association (from RQ 1.1) vary across different online courses with distinct learning designs?

**RQ 2.1** How and to what extent does engagement with different learning design elements (i.e., (a) assimilative learning activities (e.g., articles, videos), (b) communication activities (e.g., discussions), and (c) assessment activities (e.g., quizzes)) differ between learners?

**RQ 2.2** How and to what extent do temporal learning paths (i.e., sequences of learning activities) differ between learners?

**RQ 2.3** How and to what extent does engagement with different learning design elements differ between the geo-cultural contexts?

**RQ 2.4** How and to what extent does engagement with different learning design elements differ between the socioeconomic contexts?

**RQ 3.1** How and to what extent does the number of learning design elements (i.e., (a) assimilative learning activities (e.g., articles, videos), (b) communication activities (e.g., discussions), and (c) assessment activities (e.g., quizzes)) in a course predict learners' persistence?

**RQ 3.2** How and to what extent does the association between learning design elements and learner persistence (from RQ 3.1) differ between geo-cultural contexts?

**RQ 3.3** How and to what extent does the association between learning design elements and learner persistence (from RQ 3.1) differ between socioeconomic contexts?

**RQ 4.1** What are learners' perceptions of various learning design elements (i.e., activity types, predetermined path) in relation to their engagement in the course?

**RQ 4.2** In what ways do learners' perceptions (from RQ 4.1) differ between geo-cultural contexts?

The first half of this research project (Study 1 and 2) presented a dynamic picture of the role of learners' demographics and the significance of course LD in learners' progression and performance in the online learning environment.

Learners’ demographic information is generally collected during the registration process and, therefore, readily available to use in any analytics work. As outlined in Section 2.2, while several studies have used various demographic characteristics to understand learners’ achievement and
participation in a course (see Joksimović et al., 2017; Robinson et al., 2016; Kuzilek et al., 2015; Kizilcec & Halawa, 2015; Greene et al., 2015; Wladis et al., 2014; Jiang et al., 2014; Romero et al., 2013), there was a paucity in research explaining the predictive contribution of each of the characteristic towards model building when a large number of demographic characteristics are collectively used to predict learners’ performance over time. Study 1 addressed this gap by unpacking how demographic information can be used to predict learners’ performance over time, using the data from four OU courses. Overall, Study 1 highlighted that those demographic characteristics have a dynamic impact on learning outcomes over time and should be carefully considered by teachers and online course designers. The findings emphasised the importance of learners’ regional and socioeconomic contexts towards predictive model development (see Chapter 4).

Also discussed in Section 2.4, there was limited literature exploring the contextual differences in learning processes. Even more limited research to date has examined the differences across various elements of LD. Study 2 filled this gap by examining learners’ engagement with different learning design elements and their progression (i.e., learning processes) through a diverse FutureLearn MOOC. The study further explored how the engagement varies with learners’ geo-cultural and socioeconomic contexts. The findings suggested that although one individual mainstream learning path can be identified for various groups of learners, activity engagement varied mainly across the contexts (see Chapter 5).

While around first two studies discussed in this thesis (Study 1 and 2) captured a detailed picture of contextual differences in learners’ behaviours and experiences, the goal of the second two studies in this thesis (that is, Study 3 and 4) was to provide actionable insights on how to make MOOC learning environment more accommodating and welcoming for learners across the globe. As discussed in Section 2.5, a large body of research has highlighted the enrolment and participation gaps in MOOC learning environments and emphasised the need to modify courses to improve diversity and inclusiveness. However, few researchers have attempted to go beyond the holistic experiences of cross-cultural differences in learning design preferences. The thesis addressed this gap in practical knowledge through large-scale analysis of ten diverse FutureLearn MOOCs (Study 3) and then through a mixed-method study of contextual differences in learners’ perceptions of various learning design elements (Study 4). Collectively, the second half of this thesis explored the affordances as well as barriers in presumably adaptive-learning designs.

8.2 CONTRIBUTIONS TO KNOWLEDGE

This research project has provided several key contributions to the knowledge that are outlined below in bullet form.
The role of learners’ demographics in online learning. (RQ 1.1, RQ 1.2)

- Learners’ demographic characteristics can have a dynamic predictive link with the online learning outcomes over time.
- The predictive contribution of each of the characteristics varied temporally as the course progressed, as well as between different courses. This, and the above-mentioned aspects should be taken into consideration when developing a student support system to dynamically predicts students performance as the courses progress (such as Predictive Learning Analytics tools like OU Analyse (Kuzilek et al., 2017, 2015)).
- Among other characteristics, learners’ region of origin, neighbourhood poverty level, and prior education are a few of the most important and informative predictors, confirming the previous research (for example, by Kizilcec et al., (2017), Diep et al. (2016), and Allione & Stein, (2016)). This finding has implications in mitigating relevant biases in student support systems (see section 8.4 for more detail).

Learning processes and learners’ engagement with learning design elements; differences across the contexts. (RQ 2.1 to RQ 2.4)

- For behavioural analysis, it is necessary (where possible) to first categorise the learners based on their inclination towards certification. This finding was in line with Ferguson & Clow (2015), and Kizilcec et al. (2013).
- In contrast to the recent work favouring a centralised learning design (i.e., Bearman et al., 2020), this research found that the proportion of various learning design elements (activity types) in a MOOC design can significantly impact the engagement and persistence of diverse learners.
- Any modifications or alterations in learning designs should be based on the knowledge extracted from the system logs and learners’ trace data, an approach previously recommended by Winne (2017), in relation to the data-driven decision making in the educational context.
- The differences in participatory patterns across the contexts remained more prominent for the learners who never showed an intention to attain a certificate (i.e., never marked any of their activity as completed; Non-Markers).
- As was anticipated by other researchers (see Ruipérez-Valiente et al. (2020), Reich & Ruipérez-Valiente (2019)), participatory behaviour varied largely between geo-cultural and socioeconomic contexts.
Predictive link between learning design elements and persistence; Contextual differences. (RQ 3.1 to RQ 3.3)

- There is a predictive relationship between MOOC learning design elements (proportion of various types of learning activities) and learners’ persistence.
- An overall analysis of MOOC data can mask geo-cultural and socioeconomic heterogeneity in the relationship between learning design elements and learners’ persistence. The finding confirmed a concern recently raised by Ruipérez-Valiente et al. (2020).
- A change in the number of various types of learning activities may lead to precisely the opposite results for the large geo-cultural and socioeconomic subgroups in data. Not in the educational domain, but other researchers have made a case for cross-cultural and regional differences in online resource designs (see for example, Reinecke & Bernstein, 2013, 2011).
- Learners overall favoured fewer activities in MOOCs (with the sole exception of learners residing in South Asia).
- Confirming the results from previous research conducted in other areas of research (Reinecke & Bernstein, 2013, 2011), this research found that for most learners from collectivist, high PD countries from lower-middle-income regions, many video-based assimilative activities (visuals over text) in a course meant a reduced early drop out risk.
- Quantitative results suggested that communication-based activities in MOOCs worked better for the subgroup of individualists, low PD, and western learners, primarily from the English speaking or European countries with affluent economies. This finding partly confirmed the students’ help-seeking differences reported in other empirical work (e.g., Ogan et al., (2015)). The results remain somewhat in contrast with the qualitative results where regardless of the geo-cultural background, participants raised concerns around un-moderated discussions or disproportionally large number of communication-based activities.
- The same communication-based activities constrained most learners from collectivist, high PD non-English speaking countries with limited resources and lower-middle-income levels (see a previous point). This quantitative finding must be interpreted with caution as several limitations attached to the quantitative and qualitative studies may have influenced these results. The possible influence of other factors cannot be ruled out, for instance, the type of discussion (instructor-led versus user-led), the nature of the conversation (shallow conversation versus in-depth and focussed discussion around a specific topic), and other interface-design related attributes.
Learners’ perception of various learning design elements; Contextual differences. (RQ 4.1, RQ 4.2)

- Most interview participants from non-English speaking, high PD, collectivist regions reported a strong preference for a large number of video-based assimilative activities (visuals over text), a finding in line with Reinecke & Bernstein, (2013, 2011) in similar context.
- Issues that may cause occasional self-reported disinterest in video-based assimilative activities included (long) duration, speed, instructors’ accent, and low-quality visuals. Few of these issues have been briefly highlighted in previous work (see Uchidiuno et al., 2018).
- Most participants from low PD, primarily individualist regions, reported strong disfavour for clear instructional videos, deeming them too slow and slightly disengaging.
- More participants from low PD, individualist regions remained reluctant to engage in communication-based activities that were part of the course design (instructor-led discussions).
- MOOC LD with many discussion activities averted active participation of learners from non-English speaking geo-cultural regions (see for similar interesting findings, Uchidiuno et al., 2018).
- In line with (Reinecke & Bernstein, 2013, 2011), more participants from high PD, collectivist regions reported following the predetermined designed paths.
- Large number of participants reported the English language as not a substantial barrier towards learning but a factor that potentially restricts non-English speakers’ active engagement in text-based activities (both communication activities and reading material).

8.3 METHODOLOGICAL CONTRIBUTIONS

In addition to contributing to the current knowledge of contextual differences in the MOOC learning environment, this research has also made several unique methodological contributions, outlined as follows.

- Explanatory modelling using demographic variables; explanatory modelling using meaningful variables.

As discussed in detail in Chapter 3 and then in Chapter 4, LA and EDM researchers have been paying attention to one or several demographic characteristics to predict learning outcomes at a point in time (Allione & Stein, 2016; Jiang et al., 2014), or observed behavioural changes over time (see, for example, Nguyen et al., 2018; Kloft et al., 2014), but primarily leveraged engagement history or clickstream data. At the same time, most demographic information is either readily available or easily collectable. Thus, this research included a large number of demographic characteristics to predict the temporal online academic performance with decent accuracy. The research also focused
on understanding how the predictive links varied across courses from distinct disciplines. Therefore, this thesis provided a comprehensive understanding into the “dynamic” role of demographic variables on online learners’ performance over time. Generally, predictive modelling is focused more on making accurate predictions using all information that may have a predictive benefit. While this research has utilised few of the variables that were either theoretically important (in the given context) or were scientifically meaningful, several other contextual variables can be explored in future research. Overall, this research was a step towards making educational predictive models more context aware.

- **A large number of two-way interactions within survival models; implications for replication.**

This research used learning design factors to predict learners’ persistence (see Chapter 6). In the process, the approach masked heterogeneity in the diverse data. Therefore, to understand the interaction of learning design factors with the geo-cultural clusters (and later with socioeconomic clusters), a unique empirical approach was used that performed two-way interaction (terms within the survival regression equation). This method helped understand the effect of multiple covariates (four learning design factors, ten geo-cultural contexts and then four socioeconomic contexts) on persistence or survival experience (see Chapter 6 for more detail). The two-way interaction terms were used to understand the joint effect of the interacting variables on the persistence hazard profile. Overall, the method was unique and can be further extended to three-way interactions. This unique empirical approach can be instrumental in future research to understand the joint effect of learning design factors and other contextual or demographic variables.

- **Mixed-method analysis; Combination of artifact mediated study with thematic analysis and sentiment mining.**

Study 4 in this thesis used an innovative methodology when qualitative data were collected using a combination of instruments such as semi-structured interviews and artifact mediated questions (the method has been discussed in detail in Chapters 3 and 7). This research combined a commonly used qualitative data analysis method (thematic analysis) with a quantitative method for text analysis (sentiment mining). Thematic analysis results provided a detailed picture of learners’ experiences with various learning design factors, and sentiment analysis elaborated on and quantified those experiences. The approach was found to be particularly beneficial for a comparison of all seven geo-cultural contexts in the qualitative data. While there were limitations attached to the small sample size (as discussed further in this chapter), to the best of my knowledge, no research in learning sciences has used a similar mixed-method approach to the best of our knowledge. Furthermore, no research has used such a useful innovative visual method (referring to
the artefact, see Figure 7.2) to examine sensitive cultural issues (for example, acquiring certificates even through illegal means (cheating or corruption), see section 2.6.1) widely cited in previous literature.

8.4 RESEARCH LIMITATIONS AND FUTURE RESEARCH DIRECTION

This section talks through some limitations of this research that need to be acknowledged and then lays a foundation for related research work in future. Quantitative methods in general and EDM, in particular, may offer promising solutions when online learning researchers investigate voluminous data. The data usually comprise information on learners’ demographics (like age, gender, employment status) and data resulting from learners’ interaction with each other and the learning resources. However, there is a range of challenges involved at every stage, from data collection to analysis, from inferences to implications. Researchers appreciate that most data mining algorithms, if not used with caution, can fail to mitigate the biases or potentially even aggravate them (Han et al., 2011; Mannila, 2000). Therefore, instead of favouring the learners as a whole, the discriminatory results from predictive models, for example, can work against the already disadvantaged or underserved strata of the learners’ population and could further increase the overall disparity. This leaves a door wide open for further research into this domain.

It should also be acknowledged that the potential discrimination can occur at any level, from targeted marketing to communication, from enrolments to interventions. Nevertheless, there are several ways to address these issues, for instance, a fair and relatively impartial approach towards the data collection process, especially if collected via surveys. Also, opting for transparent predictive methods that provide accurate, easy to interpret results, supporting non-technical, interested laypersons. Most importantly, introducing transparency with stakeholders (enrolment managers, institutional policymakers, faculty, and students etc.) about the potential biases in data collection in model development and deployment is essential (Ekowo & Palmer, 2016).

There were several limitations associated with each of the four studies in this thesis; a few have been already discussed in the respective chapters. For example, in Study 1, the proposed models remained noticeably biased towards the majority class (Pass in this case). A different approach can be employed to understand better the role of demographic variables as a predictor of online learning outcomes, such as a larger balanced dataset with less class bias presented to effect classification modelling. A different operationalisation of success (beyond Pass, Fail, Distinction) may also yield different results. Furthermore, other contributing factors, such as learners’ temporal interaction with various learning resources, learners’ satisfaction, motivation, and a more structured cultural and socioeconomic distribution, may be assumed to propose a set of relatively comprehensive predictive models with improved quality and accuracy.
In terms of Study 2 and 3, all MOOCs used in this research were designed by the same learning design team at the OU after consultation with the instructors and subject matter experts. However, the principal limitation of the approach used here is that the researcher had no control over learning design factors. There was only one fixed, predetermined design for each MOOC. Another approach might be design-based, with a possibility of multiple learning design customisation during and between the course run. Experimental manipulation of design constructs in a course can provide causal evidence that extends beyond the correlational results presented in Study 3 (see Chapter 6). Another limitation was that all MOOCs were developed by the same university and offered via a single platform. A multi-platform analysis may also yield an enhanced understanding.

It is essential to highlight that learning design factors are a few of the many aspects linked with persistence. Further research is needed to test other potentially influencing contextual and demographic factors such as learners' age or gender. A mixed-effect model of a similar model accommodating three-way interactions may yield even more exciting results. Besides, learners' trace data alone could not provide an in-depth, comprehensive understanding of learners' individual preferences. Therefore, to explore learners' choices and learning activities preferences, the study recommended a follow-up analysis, preferably using qualitative and/or triangulated approaches (see the findings from Study 4 in Chapter 7 for one such follow-up analysis).

Study 4 in this thesis, Study 4, shares several caveats with Study 3. Collectively, both studies found many strong links between geo-cultural identities and learners' progression and their shared perception of various learning design elements and failed to address several other factors potentially affecting progression and perception. The only demographic factor that was taken into consideration was the geographic location at the geo-cultural region level (or additional socioeconomic clusters in Study 3). Several other individual and demographic factors potentially influence learners' persistence and overall experience with the course learning designs. Such factors include age, gender, education background, digital literacy level, employment status, etc. It seems reasonable to assume that these factors can be part of learners' broader cultural experiences, but these factors fall beyond the scope of current research.

Nonetheless, this generalisation based on geo-cultural or socioeconomic backgrounds could be restrictive, a limitation indicated by Baker et al. (2020), as a trap of overgeneralizing from large cultural groups to individuals. Along with these dimensions, analysing the other individual factors may yield interesting insights, as participants pointed out.
Is there a standard African learner? Do you prefer them to be hungry? Do you prefer them to be English language speaker, second speaker or third speaker? Do you prefer them to be male and unemployed or female and pregnant? (p20, Male, AF)

The research approach used in this thesis presumed all participants to be representatives of the cultural values of their country of origin. One obvious difficulty in accepting the generalisation of these traced or self-reported experiences is that the approach does not consider culturally ambiguous learners, i.e., learners born and raised in a different country while residing in another during MOOC offering or those who have been exposed extensively to other cultures. This limitation leaves the door open for future research into contextual differences in learners’ perception and persistence.

More specifically, in Study 4, all semi-structured interviews were conducted in English, while a large number of participants (16 out of 22, or 73%) were non-native English speakers. The odds remained high that those participants might have struggled to verbalise their thoughts when asked about their experiences with the learning design. Moreover, the qualitative study only analysed interview responses, whereas discussion forum text or text from the activity commenting area could provide additional information on learners’ experiences with the learning designs. An alternative mixed-method approach could also benefit from the digital language used during interactions in a course (i.e., emoji, likes/dislikes, follow/unfollow). The current studies in this thesis only focus on monolingual MOOCs, where English was the primary language of instruction. A multilingual MOOC platform, or examining MOOCs offered via regional and local platforms, or a cross-platform analysis may reveal different results.

Since this research was based on perceived usefulness, enjoyment and resulting satisfaction, there is a strong possibility that the perception changes with the context or varies with exposure, experience, gender, education level, disability status and other contextual features. This merits more in-depth research that takes account of individual characteristics, along with geo-cultural aspects. There was another methodological limitation that was attached to the study design. Even after considering delight or happiness as equivalent to enjoyment or likeness, many critical emotions will go unmentioned in the current approach. Such emotions may be closely linked with engagement or persistence, for example, panic or anxiety, despair or frustration, hope or contentment, relief or pride, anger or annoyance, and boredom or surprise (D’Mello, 2017). This aspect is particularly relevant because, in Study 4, several participants reported a certain level of

35 Participants’ opinions are their own and do not reflect author’s or supervision team’s views. None of us intended to malign an individual, community, culture, or region.
anxiety and caution when participating in a discussion, whereby non-native English speakers consistently reported this emotion.

Nonetheless, perceived enjoyment alone may not efficiently predict engagement with all types of learning activities. All these dimensions were useful but are out of the scope of this research. Also linked with the follow-up sentiment analysis, the small data size may not be sufficient to provide generalizable conclusions but merely a sense of direction. Notwithstanding the relatively limited sample, this work still offers valuable insights into learners’ perceptions of various learning design elements and their link with the respective geo-cultural contexts.

Advancements in LA/EDM have enabled algorithmic systems to support decision-making, e.g., identify and support learners at risk of failure or dropout. To increase overall model accuracy, predictive modelling often ends up making more mistakes for some groups compared to others. Recent work suggests that this failure to mitigate the potential harm that may arise due to fairness-unawareness, may disproportionately harm students from underprivileged background (Bayer et al., 2021; Nguyen et al., 2020). For example, in their recent work (Bayer et al., 2021) showed the extent to which a success prediction system deployed at the OU favoured the majority group (white male learners in this case) and erroneously predicted assignment submissions for Black, Male, Disabled learners. Mitigating these and similar algorithmic errors is critical since, otherwise, the system practically fails to alert the instructors and provide support to those who need it most.

It is, of course, important to acknowledge that there could be multiple sources of unfairness in algorithmic systems used in education (e.g., gender, age, geo-culture, poverty level), and it is impossible to fully debias the system. More research is needed to examine the factors associated with various biases as the courses progress and how they can be mitigated to improve the overall fairness in the learner-support systems. The findings from such research will support decision-makers to address the potential harm to learners from underprivileged strata that may be affected by the errors of fairness-unaware, success prediction models.

8.5 PRACTICAL IMPLICATIONS

In this thesis, Study 1 examined the role of six demographic characteristics that have been found to have a dynamic predictive link with online learning outcomes. One useful implication of Study 1 is in its implementation for institutional support. Policymakers, online learning providers, course designers and instructors all need to be aware of the varied role of specific demographic characteristics on learning outcomes throughout a particular course. One of the unique contributions of the Study 1 in this thesis is that by using the power of DTs in elaborating models, this approach provides exhaustive information to stakeholders helping them to foresee how learners from different regions, socioeconomic strata, or prior education, behave and achieve
differently in each course. The process also provides actionable insights into adopting a tailored approach towards a personalized student support system while providing additional support to students at risk of failure by introducing timely interventions and other similar measures.

Interestingly, key predictive factors vary with time and courses, suggesting that LA and EDM researchers should be mindful of their approaches when analysing the temporal dynamics of online learning. As discussed in the previous section, future work could further extend the analysis done in Study 1, using more data from other large online learning courses from a variety of academic disciplines. However, the ethical considerations of such implications remain a topic of interest to future researchers and us.

As mentioned earlier in this thesis, success in MOOCs is relative. Without a deep knowledge of learners’ navigation through the system, it would remain hard to distinguish between good and bad decisions. This left a door open to further research on learners’ experiences. i.e., while navigating the course, how are they making these decisions to engage more with one or the other type of activity. The subsequent study, Study 2, contributed to the field by interrogating the behaviour of learners while considering different categories that go beyond simply looking at those who completed a substantial fraction of the course or those who dropped out. Study 2 can be beneficial for practice in MOOC learning design and suggested that analyses of voluminous data being captured and stored in MOOC clickstream logs require innovative methods, such as process mining and variant mapping. Such methods intrinsically support the exploration of learners’ behaviour hidden in voluminous data.

Study 2 also highlighted the extent to which the participatory behaviour varied between geocultural and socioeconomic contexts. In particular, the results highlighted the dissimilarities between activity access behaviour of large geo-cultural and socioeconomic subgroups. The study argued that such dissimilarities should be taken into consideration while designing a MOOC. Despite its exploratory nature, Study 2 laid the groundwork for future research into behavioural modelling and mapping within the MOOC learning environment. Further investigation was needed to understand what factors could explain these differences in how learners from different contexts might engage with the four types of activities? One potential direction was exploring the correlational link between learner’s participatory behaviour and learning design aspects (such as learning activity types) (this aspect was partially addressed in Study 3 and Study 4 as discussed in Chapters 6 and 7, respectively). Still, as noted in the previous section, more contextual information could support future researchers to establish a greater degree of accuracy on this matter.

The following study, Study 3, examined the link between learning design factors and learners’ persistence. Overall, the study provided an evidence-based understanding of learner experiences from different geo-cultural and socioeconomic backgrounds and related those experiences with the
proportion of course content type. This evidence has implications for developing culturally adaptive MOOC designs. Therefore, the key contribution of this research was that the findings informed context-centred design. Indeed, by offering learners a choice to opt for such an adaptive course layout, we can ensure that the design is still learner-centred and not merely context-centred. This innovative research provided new insight into cultural variation in learning design preferences that inform ongoing efforts to create effective online learning environments for people from diverse backgrounds.

The collective results from the second part of this thesis (Study 3 and 4) led us to two interesting directions as follows. First, comparing the overall data analysis and subgroup analysis suggested that the overall data analysis mirrored the patterns later occurred in the largest subgroup (Anglo-Saxon group in this case). Also, precisely opposite results were received for the second-largest subgroup (South Asian group), while the third-largest subgroup (learners from Sub-Saharan African countries) analysis also revealed distinct patterns, entirely different from the rest of the subgroups. That implies that decisions driven from an overall data analysis would only support the largest subgroup while impeding the persistence of learners from other small, underrepresented geo-cultural regions. The decision-makers (for example, instructors, learning designers, institutional policymakers, and MOOC providers) should be wary of this exclusion bias and the discrimination that may potentially occur in favour of the dominant subgroup. Statistical sciences and machine learning methods offer several ways to deal with this issue, but those methods are out of the scope of this research.

Second, the research found no perfect recipe for a MOOC design that works for all learners worldwide. The overarching findings suggested that the link between persistence and changes in learning design (changing the number of various activities) varied with geo-cultural contexts. Perhaps there is no ideal combination of learning activities that facilitate learners from all around the world. This research explains why there is no single, universal learning design for MOOC that can work for all learners. It was found that a fixed, predetermined learning design can hardly be inclusive. Interestingly, the qualitative results (see Study 4 discussed in Chapter 7) echoed and elaborated on the quantitative findings (see Study 3 discussed in Chapter 6).

This research contributed to our understanding of learners’ experiences with various types of learning activities and the association between the number of various types of activities and persistence. This key contribution has implications towards developing (several) learning designs for the massive open online learning environment. Until we reach the (difficult yet attainable) milestone of a flexible, culturally adaptive MOOC learning design, this research recommends taking a balanced approach by combining all types of learning activities, not just video-based or reading MOOCs.
A note of caution is due here since there may be some risks associated with these implications. First and foremost, providing learners with their preferred activities only (for example, videos and quizzes only) and tailoring learning design to improve learner persistence in a course may be limiting for affective, behavioural, and/or cognitive growth. Even the most personalized LD should be guided by established learning design theories and may not be optimal for each and every learner. In addition, learners' self-reported preferences may be used as one of the many design guideposts. While Study 3 examined the predictive link between learning design elements and persistence, study 4 hypothesized that increasing learning activities for the specific context may increase engagement. There is no evidence that learning from the preferred activity type (reading, video watching) actually supports learning.

In addition, although the literature on culturally adaptive UX/UI (as reported in Chapter 2) has identified different design-construct preferences across the contexts, UX/UI developed in one context may be biased in relation to the other context. However, it is still unknown whether adapting to user preferences will mitigate respective biases or reinforce them and, consequently, augment the East-West polarization and contribute to further divisions. Keeping learners exposed to a broad range of learning design elements embedded in evidence-based theory may de-escalate this polarization and open new opportunities to learn from. In line with Hofstede (1986), the 'burden of adaptation' in cross-cultural learning situations (such as those in MOOCs) should be primarily on the instructors, learning designers and MOOC providers. Therefore, only after several implementations of multiple learning designs in online learning will we be able to explore if and whether the recommendations from this mixed-method research have stood the test of time.

In conclusion, while it should be acknowledged that designing localised or culturally adaptive versions of free online courses may not always be cost-effective, this research still recommends moving away from one-size-fits-all MOOC designs. Mainstream MOOC providers may need to take the recent advancements in learning technology as an opportunity to design a more culturally adaptive, modifiable open online learning environment that facilitates the needs of diverse learners worldwide, not automatically perhaps, but only if opted for.

8.6 CONCLUDING REMARKS
The abstract of this thesis indicates how this research has only solved one part of the jigsaw. A previous section in this chapter has already discussed several limitations attached to this research. When I first started writing this thesis, I felt proud of this work, without any doubt a pioneer work in cross-cultural research in MOOC learning environments. Nevertheless, towards the end of the thesis writing, reality sank in. I gradually realised how a multitude of questions had remained unanswered. On an interesting note, I noticed how I started my PhD journey as a quantitative researcher and somewhere on my way, I got converted and became a mixed-method researcher.
On a personal level, I have now started paying more attention to the multidimensional nature and complexity of learning behavioural modelling. To keep it precise, I realised how challenging it could be to develop a MOOC design that adapts to the broader needs of learners from different contexts, recognising the differences in learning behavioural preferences; however, may be a good starting point.
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Appendix A (For Chapter 2 and 3)

The following extract best explains GLOBE study taxonomy in relation to the previous work in cultural research, mainly using Hofstede’s NCD and McClelland’s Need theory of motivation as a baseline: "GLOBE effectively split two of Hofstede's dimensions into a total of four, first turning Masculinity into Gender Egalitarianism and Assertiveness. Next, Individualism, after choosing the label of its opposite pole, into two types of Collectivism: institutional and in-group. They kept the labels and dimensions of Power Distance and Uncertainty Avoidance, but adjusted the way in which they are measured, particularly Uncertainty Avoidance. Humane and Performance Orientation are derived most directly from McClelland (1985), and Future Orientation, while sounding similar to Hofstede's Long-term Orientation, is derived more directly from Kluckhohn & Strodtbeck's work in 1961 on Past, Present, and Future Orientation” (Hofstede, 2006).

Figure A 2.1 Visual Epistemology of GLOBE Dimensions (Hadwick, 2011)
Table A.2.1 The Extended-GLOBE List of Variables

<table>
<thead>
<tr>
<th>Ethnicity</th>
<th>American Indian, African Black, European Caucasian, Arabic, Other Middle Eastern, Indian (East), Chinese, Other Asian, Pacific Islander, Mixed Race (two or more ethnic groups), OTHER Not specifically identified in source</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Religion</strong></td>
<td>Percent of population classified as Christian Protestant (including Pentacostals), Catholic or Orthodox Christian, Buddhist, Islamic faith, Hindu faith, Confucian philosophy, Other Religions (including No religion)</td>
</tr>
<tr>
<td><strong>Official Languages</strong></td>
<td>Arabic, English, French, Spanish, Chinese, Russian, Portuguese</td>
</tr>
<tr>
<td><strong>Regions of the World</strong></td>
<td>Sub-Saharan Africa, Middle East and North Africa, Western Europe, Northern Europe, Central Europe, South-Eastern Europe, Southern Europe, Central Asia, South-Eastern Asia, North America, Central America, Caribbean Region, South America, Oceania</td>
</tr>
<tr>
<td><strong>Native Languages</strong></td>
<td>Arabic, English, French, Spanish, Scandinavian, Germanic subgroup of languages, Slavic subgroup of languages, Creole (all versions), Hindi, Mandarin Chinese, Afro-Asiatic group of languages, Altaic group of languages, American Indian group of languages (includes many independent groups), Austronesian group of languages, Indo-European group of languages (excluding those specifically identified above), Indo-Iranian group of languages, Indo_Iranian and Dravidian groups of languages, Niger-Congo and Nilo-Saharan group of languages, Romance subgroup of languages (excluding French and Spanish listed above already), Sini-Tibetan group of languages, Uralic and Caucasian groups of languages</td>
</tr>
<tr>
<td><strong>Other Variables</strong></td>
<td>Dummy variable for British &quot;special relationship&quot;.</td>
</tr>
<tr>
<td></td>
<td>Latitude of country's capital, Longitude of country's capital</td>
</tr>
<tr>
<td>Concept, intended use</td>
<td>Groupings</td>
</tr>
<tr>
<td>-----------------------</td>
<td>-----------</td>
</tr>
<tr>
<td>Income, analytical</td>
<td>Low, Lower Middle, Upper Middle, High</td>
</tr>
<tr>
<td>Human Development, analytical</td>
<td>Very High, High, Medium, Low</td>
</tr>
<tr>
<td>Development, analytical</td>
<td>Developed and Developing Regions</td>
</tr>
</tbody>
</table>
Appendix B (For Chapter 4)

### Table B 4.1
Region Names

<table>
<thead>
<tr>
<th>Region</th>
<th>Replaced</th>
</tr>
</thead>
<tbody>
<tr>
<td>East Anglian Region</td>
<td>EA</td>
</tr>
<tr>
<td>East Midlands Region</td>
<td>EM</td>
</tr>
<tr>
<td>Ireland</td>
<td>Ir</td>
</tr>
<tr>
<td>London</td>
<td>L</td>
</tr>
<tr>
<td>North Region</td>
<td>N</td>
</tr>
<tr>
<td>North Western Region</td>
<td>NW</td>
</tr>
<tr>
<td>Scotland</td>
<td>Sc</td>
</tr>
<tr>
<td>South East Region</td>
<td>SE</td>
</tr>
<tr>
<td>South Region</td>
<td>S</td>
</tr>
<tr>
<td>South West Region</td>
<td>SW</td>
</tr>
<tr>
<td>Wales</td>
<td>W</td>
</tr>
<tr>
<td>West Midlands Region</td>
<td>WM</td>
</tr>
<tr>
<td>Yorkshire Region</td>
<td>Y</td>
</tr>
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</table>

### Table B 4.2
IMD Bands

<table>
<thead>
<tr>
<th>IMD Band</th>
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</tr>
</thead>
<tbody>
<tr>
<td>-</td>
<td>NA</td>
</tr>
<tr>
<td>0-10 %</td>
<td>L1</td>
</tr>
<tr>
<td>10-20 %</td>
<td>L2</td>
</tr>
<tr>
<td>20-30 %</td>
<td>L3</td>
</tr>
<tr>
<td>30-40 %</td>
<td>L4</td>
</tr>
<tr>
<td>40-50 %</td>
<td>L5</td>
</tr>
<tr>
<td>50-60 %</td>
<td>L6</td>
</tr>
<tr>
<td>60-70 %</td>
<td>L7</td>
</tr>
<tr>
<td>70-80 %</td>
<td>L8</td>
</tr>
<tr>
<td>80-90 %</td>
<td>L9</td>
</tr>
<tr>
<td>90-100%</td>
<td>L10</td>
</tr>
</tbody>
</table>

### Table B 4.3
Level of Education

<table>
<thead>
<tr>
<th>Level of Education</th>
<th>Replaced</th>
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</thead>
<tbody>
<tr>
<td>Lower Than A Level</td>
<td>LA</td>
</tr>
<tr>
<td>A Level or Equivalent</td>
<td>A</td>
</tr>
<tr>
<td>HE Qualification</td>
<td>HE</td>
</tr>
<tr>
<td>Post Grad Qualification</td>
<td>PG</td>
</tr>
<tr>
<td>No Formal Qualification</td>
<td>NF</td>
</tr>
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### Table B 4.4
Age Band

<table>
<thead>
<tr>
<th>Age band</th>
<th>Replaced</th>
</tr>
</thead>
<tbody>
<tr>
<td>0-35 years</td>
<td>A1</td>
</tr>
<tr>
<td>36-54 years</td>
<td>A2</td>
</tr>
<tr>
<td>55&lt;= years</td>
<td>A3</td>
</tr>
</tbody>
</table>
Table C 5.1 Frequency and relative frequency of access for individual activity type.

<table>
<thead>
<tr>
<th>Activity Type</th>
<th>Activity Distribution</th>
<th>Frequency</th>
<th>Rel. freq. of access (%)</th>
<th>Frequency</th>
<th>Rel. freq. of access (%)</th>
<th>Frequency</th>
<th>Rel. freq. of access (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Assimilative_Article</td>
<td>44 (64.7%)</td>
<td>13,883</td>
<td>65.42</td>
<td>12,354</td>
<td>65.79</td>
<td>1,112</td>
<td>49.14</td>
</tr>
<tr>
<td>Communication_Discussion</td>
<td>12 (17.6%)</td>
<td>3,806</td>
<td>17.94</td>
<td>3,287</td>
<td>17.5</td>
<td>230</td>
<td>10.16</td>
</tr>
<tr>
<td>Assimilative_Video</td>
<td>8 (11.7%)</td>
<td>2,523</td>
<td>11.89</td>
<td>2,341</td>
<td>12.47</td>
<td>867</td>
<td>38.31</td>
</tr>
<tr>
<td>Assessment_Quiz</td>
<td>3 (4.4%)</td>
<td>965</td>
<td>4.55</td>
<td>780</td>
<td>4.15</td>
<td>51</td>
<td>2.25</td>
</tr>
<tr>
<td>Assessment_Test</td>
<td>1 (1.5%)</td>
<td>43</td>
<td>0.2</td>
<td>17</td>
<td>0.09</td>
<td>3</td>
<td>0.13</td>
</tr>
</tbody>
</table>
Table C 5.2 Most common subgroups within three primary group of learners.

<table>
<thead>
<tr>
<th>Subgroups</th>
<th>Markers</th>
<th></th>
<th>Partial-Markers</th>
<th></th>
<th>Non-Markers</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Cases (449)</td>
<td>Events</td>
<td>Cases (832)</td>
<td>Events</td>
<td>Cases (805)</td>
<td>Events</td>
</tr>
<tr>
<td>V1</td>
<td>141(31.4%)</td>
<td>67</td>
<td>73(8.77%)</td>
<td>2</td>
<td>545(67.7%)</td>
<td>1</td>
</tr>
<tr>
<td>V2</td>
<td>44(9.8%)</td>
<td>16</td>
<td>44(5.29%)</td>
<td>3</td>
<td>80(9.94%)</td>
<td>2</td>
</tr>
<tr>
<td>V3</td>
<td>28(6.24%)</td>
<td>1</td>
<td>31(3.73%)</td>
<td>4</td>
<td>28(3.48%)</td>
<td>3</td>
</tr>
<tr>
<td>V4</td>
<td>19(4.23%)</td>
<td>68</td>
<td>31(3.73%)</td>
<td>6</td>
<td>23(2.86%)</td>
<td>1</td>
</tr>
<tr>
<td>V5</td>
<td>13(2.9%)</td>
<td>34</td>
<td>28(3.37%)</td>
<td>7</td>
<td>8(0.99%)</td>
<td>2</td>
</tr>
<tr>
<td>V6</td>
<td>11(2.45%)</td>
<td>50</td>
<td>25(3%)</td>
<td>5</td>
<td>7(0.87%)</td>
<td>4</td>
</tr>
<tr>
<td>V7</td>
<td>10(2.23%)</td>
<td>65</td>
<td>23(2.76%)</td>
<td>16</td>
<td>6(0.75%)</td>
<td>5</td>
</tr>
<tr>
<td>V8</td>
<td>8(1.78%)</td>
<td>4</td>
<td>23(2.76%)</td>
<td>67</td>
<td>5(0.62%)</td>
<td>1</td>
</tr>
<tr>
<td>V9</td>
<td>7(1.56%)</td>
<td>3</td>
<td>22(2.64%)</td>
<td>8</td>
<td>4(0.5%)</td>
<td>6</td>
</tr>
<tr>
<td>V10</td>
<td>7(1.56%)</td>
<td>68</td>
<td>21(2.52%)</td>
<td>9</td>
<td>4(0.5%)</td>
<td>3</td>
</tr>
<tr>
<td>V11</td>
<td>4(0.89%)</td>
<td>2</td>
<td>14(1.68%)</td>
<td>10</td>
<td>3(0.37%)</td>
<td>14</td>
</tr>
<tr>
<td>V12</td>
<td>4(0.89%)</td>
<td>6</td>
<td>14(1.68%)</td>
<td>66</td>
<td>3(0.37%)</td>
<td>2</td>
</tr>
<tr>
<td>V13</td>
<td>4(0.89%)</td>
<td>8</td>
<td>12(1.44%)</td>
<td>11</td>
<td>3(0.37%)</td>
<td>2</td>
</tr>
<tr>
<td>V14</td>
<td>4(0.89%)</td>
<td>9</td>
<td>12(1.44%)</td>
<td>34</td>
<td>2(0.25%)</td>
<td>7</td>
</tr>
<tr>
<td>V15</td>
<td>4(0.89%)</td>
<td>67</td>
<td>11(1.32%)</td>
<td>13</td>
<td>2(0.25%)</td>
<td>9</td>
</tr>
</tbody>
</table>
### Table C 5.3

<table>
<thead>
<tr>
<th>Metric: Activity access behaviour</th>
<th>AF</th>
<th>AS</th>
<th>CA</th>
<th>EE</th>
<th>GE</th>
<th>LA</th>
<th>LE</th>
<th>ME</th>
<th>NE</th>
<th>SA</th>
<th>Chi-Square</th>
<th>Df</th>
<th>P</th>
</tr>
</thead>
<tbody>
<tr>
<td>Overall</td>
<td>9</td>
<td>14</td>
<td>9</td>
<td>9</td>
<td>9</td>
<td>33</td>
<td>10</td>
<td>5</td>
<td>6</td>
<td>8</td>
<td>76.97</td>
<td>9</td>
<td>6.43E-13</td>
</tr>
<tr>
<td>Video</td>
<td>1</td>
<td>2</td>
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Figure C 5.2
Figure C 5.3

Figure C 5.4
Figure C 5.5

Figure C 5.6
Figure C 5.7

Figure C 5.8
Appendix D (For Chapter 6)

Figure D 6.1. KM curves illustrating the differences between survival probabilities with respect to activities accessed for ten cc subgroups. The risk table shows absolute number of learners, and the percentage of learners at risk by that point.

Figure D 6.2. KM curves illustrating the differences between survival probabilities for four sec subgroups.
Appendix E (For Chapter 7)

Participants Consent Form

Project title: Investigation of Temporal Dynamics in MOOC Learning Trajectories; a Geo-cultural Perspective

Current study title: Making MOOCs culturally inclusive; keeping a promise

Saman Rizvi, PhD student, IET, The Open University
Prof Bart Rienties, IET, The Open University

Please write Yes or No for each of the following statements.

1. Taking part in the study

I have read and understood the study information dated [____], or it has been read to me. I have been able to ask questions about the study and my questions have been answered to my satisfaction.

I consent voluntarily to be a participant in this study and understand that I can refuse to answer questions and I can withdraw from the study at any time up until 90 days after this interview, without having to give a reason.

I understand that taking part in the study involves sharing my experience and perception about OU FutureLearn MOOC learning design. I agree to the interview being audio-recorded.

I understand that I will be given a link to Amazon voucher of £20 for participating in this interview.

2. Use of the information in the study

I understand that information I provide will be used for presentation, book chapter, conference paper, or journal paper.

I understand that personal information collected about me that can identify me, such as my name or where I live, will not be shared beyond the study team.
I understand that my data will be stored with confidentiality for up until the end of 2024, after which it will be destroyed.

I understand that the extracts of audio recording from this interview will be used for analysis, from which however, I will not be identifiable. The analysis done on anonymised data may be further disseminated in the form of presentation, book chapter, conference paper, or journal paper.

3. Future use and reuse of the information by others

I give permission for the audio recording from the interview to be deposited in a specialist data centre after it has been anonymised, so it can be used for future research and learning.

I give permission for the de-identified (anonymised) transcripts to be deposited in a specialist data centre after it has been anonymised, so it can be used for future research and learning.

4. Signatures

Name of participant [IN CAPITALS]  Signature  Date

I have witnessed the accurate reading of the consent form with the potential participant and the individual has had the opportunity to ask questions. I confirm that the individual has given consent freely.

Name of participant [IN CAPITALS]  Signature  Date

This research project [title: Investigation of Temporal Dynamics in MOOC Learning Trajectories; a Geo-cultural Perspective.] has been reviewed by, and received a favourable opinion, from the OU Human Research Ethics Committee - HREC reference number: HREC/2842/Rizvi

http://www.open.ac.uk/research/ethics/
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1. Follow LD vs Don’t follow (L1 vs L2)
2. No Discussion vs Discussion (L7 vs L8)

**Response:** Strong preference for OR A general preference for OR Found strongly relatable, (NP=no preference)

**Highest Education:** Bachelor’s degree (B), Master’s degree (M), Doctoral/professional degree (D)

**Exposure to other cultures/regions:** Extensive (Ex), Brief (Br)

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251
### Cultural dimension: Collectivism [Text vs Video]

<table>
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<tr>
<th>C grp</th>
<th>Partic. #</th>
<th>Education</th>
<th>Exposure to other cultu</th>
<th>Behaviour</th>
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<td>L3+L4 (text + visual)</td>
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### Cultural dimension: Collectivism [Competence vs certification]

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Q1A: Why attended? Q1B: Most favourite part in course, Q1C: Least favourite part in course:

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<tr>
<th></th>
<th>Q1A: Why attended?</th>
<th>Q1B: Least favourite part in this MOOC</th>
<th>Q1C: Most favourite part in this MOOC</th>
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<tr>
<td></td>
<td>Professional development</td>
<td>Lack of instructors’ involvement / support / engagement in course discussions.</td>
<td>Collaborative activity in hybrid learning environment (MOOC used in hybrid f2f)</td>
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<tr>
<td>P1 (LA)</td>
<td>Professional development + Academic development</td>
<td>Lack of engagement from both sides, need better assessment methods (graded, pass/fail)</td>
<td>Openness, accessibility, clarity of content</td>
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<td>P2 (SA)</td>
<td>Professional development</td>
<td>Discussion steps (feel weird)</td>
<td>Subtitles provided with videos</td>
</tr>
<tr>
<td>P3 (AS)</td>
<td>Professional development</td>
<td>Discussion steps (are not necessary)</td>
<td>No deadlines, self-paced learning</td>
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<tr>
<td>P4 (SA)</td>
<td>Professional development + personal interest</td>
<td>Time restriction (short expiry date), Lack of instructors’ involvement/engagement in course</td>
<td>Intrinsic interactivity in course content, possibility of engagement</td>
</tr>
<tr>
<td>P5 (AS)</td>
<td>Personal interest + hobby</td>
<td>another part of the course where they interviewed individuals; it was useless</td>
<td>One part of the course where they interviewed individuals; it was useful</td>
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<tr>
<td>P6 (SA)</td>
<td>Professional development</td>
<td>Bad video quality</td>
<td>Course structure; well-structured course</td>
</tr>
<tr>
<td>P7 (ME)</td>
<td>Academic development</td>
<td>Peer assessment, wanted someone more knowledgeable/expert to assess my work</td>
<td>Videos were short but informative and clear, Good combination of text &amp; videos</td>
</tr>
<tr>
<td>P8 (ME)</td>
<td>Professional development</td>
<td>Videos were too short, I prefer long lecture like videos, not 3 or 4 min long</td>
<td>Documents (rich articles) and more useful article links within those articles</td>
</tr>
<tr>
<td>P9 (ME)</td>
<td>Personal interest</td>
<td>Lack of instructors’ involvement / support / engagement in course. Lack of presence of Subject matter expert</td>
<td>Couple of articles (not long but succinct, provided with learning objectives)</td>
</tr>
<tr>
<td>P10 (EE)</td>
<td>Personal interest</td>
<td>Live support from instructor was unavailable. Software in the course was too technical to understand on my own.</td>
<td>Relevant content</td>
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<tr>
<td>P11 (AS)</td>
<td>Academic development</td>
<td>N/A</td>
<td>N/A</td>
</tr>
<tr>
<td>P12 (AS)</td>
<td>Academic development + personal interest</td>
<td>Fee. Badge was only available after fee where it was advertised as free course</td>
<td>Contributors, Interesting Content as it was generated in different contexts.</td>
</tr>
<tr>
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<td>-----------------------------------------------------------------------------</td>
<td>--------------------------------------------------------------------------</td>
</tr>
<tr>
<td>P13 (AS)</td>
<td>Professional development</td>
<td>Some course steps were quite long! (he prefers short steps)</td>
<td>Diversity in learners, diversity in the course</td>
</tr>
<tr>
<td>P14 (SA)</td>
<td>Professional development</td>
<td>Articles or reading parts (boring) especially when reading from browser</td>
<td>Videos (felt like f2f learning)</td>
</tr>
<tr>
<td>P15 (AF)</td>
<td>Professional development + personal interest</td>
<td>-</td>
<td>Interface design, good combination of various types of learning activities</td>
</tr>
<tr>
<td>P16 (GE)</td>
<td>Personal interest</td>
<td>Format and line spacing made it difficult to read, prefers more flexible interface</td>
<td>Some videos were good (normally hate learning from videos)</td>
</tr>
<tr>
<td>P17 (AS)</td>
<td>Professional development</td>
<td>Unstructured comments in discussion</td>
<td>Good combination of text &amp; videos</td>
</tr>
<tr>
<td>P18 (EE)</td>
<td>Personal interest</td>
<td>Some parts of the course like some videos were unnecessarily long</td>
<td>Some parts of the course (on gender in sports), relevant and useful discussion</td>
</tr>
<tr>
<td>P19 (LA)</td>
<td>Academic development</td>
<td>Course had lots of articles, it could use more videos and increased interactivity</td>
<td>Taking quizzes after videos</td>
</tr>
<tr>
<td>P20 (AF)</td>
<td>Professional development + personal interest</td>
<td>Discussion as always had a feeling of catching up with discussions</td>
<td>Course content</td>
</tr>
<tr>
<td>P21 (EE)</td>
<td>Professional development + personal interest</td>
<td>Reading articles</td>
<td>Student cantered design, no deadlines, self-pace learning, open-ended but practical weekly assignments were given</td>
</tr>
<tr>
<td>P22 (SA)</td>
<td>Academic development + personal interest</td>
<td>-</td>
<td>Some parts of the course where they explained a certain process, some videos</td>
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</table>
## Q2: Learning design as Learning design pathway

<p>| | | |</p>
<table>
<thead>
<tr>
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<tbody>
<tr>
<td>P1 (LA)</td>
<td><strong>Follow/Linear</strong></td>
<td>Mainly follow the pathway but it depends why I am taking the MOOC? (skipping the activity = risky. Go forward in linear manner step by step, but sometimes go back to revise or revisit some activity)</td>
</tr>
<tr>
<td>P2 (SA)</td>
<td><strong>Both</strong></td>
<td>Follow the pathway = If unfamiliar with content, lack of background knowledge, beginner. Choose and pick = If familiar with content, with intermediate to advance background knowledge.</td>
</tr>
<tr>
<td>P3 (AS)</td>
<td><strong>Follow/Linear</strong></td>
<td>Maximal structure. I follow it as the instructor is designed it. So, I go through step by step. In all courses, I always kind of follow it that way.</td>
</tr>
<tr>
<td>P4 (SA)</td>
<td><strong>Follow/Linear</strong></td>
<td>Always watch the videos first. Follow the list of videos that are recommended by the instructor and follow the pathway designed by the instructors, except for discussions and articles and [other] unnecessary things that are not required to complete the course.</td>
</tr>
<tr>
<td>P5 (AS)</td>
<td><strong>Follow/Linear</strong></td>
<td>Someone has put the effort into take you through a certain way, then it’s probably best to stick with that. Left to my own devices, I might be a little bit less organised, especially with these courses that I did appreciate the pace, the direction, and just building on small blocks.</td>
</tr>
<tr>
<td>P6 (SA)</td>
<td><strong>Follow/Linear</strong></td>
<td>The course is designed by the experts, they design it from the basic to the advanced level...So it's better to go with the designed course [course design]...[but] if the course is starting from the basic knowledge and I already know that? then I would prefer to go forward to find something in the course instead of following the basic design.</td>
</tr>
<tr>
<td>P7 (ME)</td>
<td><strong>Both</strong></td>
<td>Depends on the course (background knowledge and topic/discipline familiarity). Technical course = Follow the design. Social science/Educational science (which I am more familiar with) = Choose my own design. If video-based course, go to the videos directly.</td>
</tr>
<tr>
<td>P8 (ME)</td>
<td><strong>Follow/Linear</strong></td>
<td>Like following the predetermined learning pathway. Otherwise, I feel like I missed something. And I feel like if I skip a few exercises or like sessions, I will find it difficult to complete tasks in the following sessions. Don’t like skipping sessions or skipping, like exercises. I like going in order.</td>
</tr>
<tr>
<td>P9 (ME)</td>
<td><strong>Non-Linear</strong></td>
<td>It depends on the subject that I want to learn. So, that means, ... depends on the type or the kind of MOOC that I want to join it. Depends on the topic or discipline or subject area.</td>
</tr>
<tr>
<td>P10 (EE)</td>
<td><strong>Non-Linear</strong></td>
<td>Like I know each moment where, I what I have to do in each step (Article, video, etc.). So, I like this.</td>
</tr>
<tr>
<td>ID</td>
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<td>Description</td>
</tr>
<tr>
<td>-----</td>
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<td>-------------------------------------------------------------------------------------------------------</td>
</tr>
<tr>
<td>P11</td>
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<td>It was too much material. So, I basically picked and selected what I thought was going to be most interesting. So it wasn't strictly speaking linear.</td>
</tr>
<tr>
<td>P12</td>
<td>Non-Linear</td>
<td>I do jump around. So, I wouldn't say it's I wouldn't say it's completely linear... And in some ways it makes you feel as if you have some control over what you're learning, rather than having a path imposed.</td>
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<tr>
<td>P13</td>
<td>Non-Linear</td>
<td>Generally, I tend to pick and choose</td>
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</table>
| P14 | Follow/Linear| Mostly I just try to move according to the design... like a list of activities they have developed. So, I just like to go point wise only so that I can have a good knowledge of the next topic accordingly.  
I would like to go as per the instructor only because that person has designed the course. So [they must have designed] in a particular structured way... If I go [for] my own path, I [may] skip the things so I might not get learning achievement accordingly. |
| P15 | Follow/Linear| Personally, I followed the design so I could follow the activities during the run and without skipping them. |
| P16 | Non-Linear   | Oh no, I don't do authority so I just kind of graze and skip through it and click through it and just see what piques my interest read a page and click on or back or randomly... I don't follow a set pathway, ever. I am, definitely someone who finds her own route through things. |
| P17 | Follow/Linear| I really like having a predetermined path. And one of the things I liked about this course was that it was very, very clear up front which activities were going to happen each week and how long each would take. And that's the way I like to work and I like to learn. I like to know exactly what I've got to get done. And I get that sense of achievement from having, you know, ticked off another task, another two tasks so, for me something very structured works much better and is much more enjoyable than something where it's just here it all is have a look at it, decide what you want to do. |
| P18 | Follow/Linear| I generally follow, you know, each section by section. So, I do follow that the path that the educators defined. But I do go back sometimes to find, to refresh my memory around some stuff, or to revisit the resource I found interesting, and I didn't necessarily have enough time |
| P19 | Both         | Follow the pathway = If unfamiliar with content, lack of background knowledge, beginner.  
Choose and pick = If familiar with content, with intermediate to advance background knowledge. |
| P20 | Follow/Linear| Normally, normally, I would follow the design.                                                   |
| P21 | Follow/Linear| I would usually just follow the learning path. I think it makes thing it makes more sense. Someone has actually spent a lot of time thinking about the layout, thinking about the procedure of the learning outcomes |
so. I could sometimes skip a few things if I find them that they’re, you know, not relevant to me. But I would definitely follow the pathway.

| P22 (SA) | Follow/Linear | Generally, yes, generally I follow this approach (follow the design and pathway). |
### Q3A, Q3B: Least vs Most enjoyable activity type among article, video, quiz, discussion (instructor-led)

<table>
<thead>
<tr>
<th></th>
<th>Least favourite learning activity</th>
<th>Most favourite learning activity</th>
</tr>
</thead>
<tbody>
<tr>
<td>P1 (LA)</td>
<td>Discussion (see no purpose!)</td>
<td>Quizizes</td>
</tr>
<tr>
<td></td>
<td>Videos (But likes interactive video, quiz embedded in V)</td>
<td>Articles</td>
</tr>
<tr>
<td>P2 (SA)</td>
<td>Articles</td>
<td>Videos (prefers interactive videos)</td>
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<td>P6 (SA)</td>
<td>Articles (Boring, not important, waste of time, not fond of reading)</td>
<td>Videos (short yet informative, concise, easy to learn from)</td>
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<td>P7 (ME)</td>
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<td>Discussion (engage and motivate learners)</td>
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<tr>
<td>P8 (ME)</td>
<td>Discussion (Comments: I would avoid if not necessary), unfamiliarity with others, lack of agency on comments</td>
<td>Videos (Short but informative)</td>
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<td>Quizizes (helpful)</td>
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<tr>
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<td>Discussion (structure of discussion steps confusing), no presence of instructor/subject matter expert in Discuss</td>
<td>Articles (along with learning objectives)</td>
</tr>
<tr>
<td>P11 (AS)</td>
<td>Videos (when you're forced to watch a video sometimes, I don't know, it wasn't the best video to watch. So even though the topic was really relevant, I didn't particularly love the videos. So I would have preferred to have read the material first.)</td>
<td>Articles (I didn't particularly want to watch the video. It was going to take too long to watch the video. So, I just perhaps went straight to read the script or the video which I read much quicker than watching the whole video. And to me, that was a lot easier.)</td>
</tr>
</tbody>
</table>

<p>|                | Quizizes (Quizzes are too general!)                                    | |</p>
<table>
<thead>
<tr>
<th>Page</th>
<th>Discussion</th>
<th>Quizzes</th>
<th>Videos</th>
</tr>
</thead>
<tbody>
<tr>
<td>P12 (AS)</td>
<td>(I think you are supposed to be on your own in a MOOC so why instructor-led discussion steps?)</td>
<td></td>
<td>(give you a sense of fun)</td>
</tr>
<tr>
<td>P13 (AS)</td>
<td>(not dislike, but don’t enjoy them either) Articles (Less engaging, not fond of dense reading)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>P14 (SA)</td>
<td>Articles (or other textual material, not enjoyable activity)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>P15 (AF)</td>
<td>Articles (not dislike but not particularly enthusiastic about articles)</td>
<td></td>
<td>Videos</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Discussion</td>
</tr>
<tr>
<td>P16 (GE)</td>
<td>Discussion (feels exposed in MOOCs)</td>
<td>Mixed</td>
<td>(videos if they are not talking-head type which is common, don’t show instructor in vid!)</td>
</tr>
<tr>
<td>P17 (AS)</td>
<td>Discussion (So many people, so many different views, hard to make any sense, lots of noise)</td>
<td></td>
<td>Videos</td>
</tr>
<tr>
<td>P18 (EE)</td>
<td>Videos (In this MOOC b/c they were long and less interactive just like long lecture, prefers short and interactive videos)</td>
<td></td>
<td>Discussion</td>
</tr>
<tr>
<td></td>
<td></td>
<td>[Later in the interview] I prefer video or visuals, because I found them more engaging</td>
<td></td>
</tr>
<tr>
<td>P19 (LA)</td>
<td>Discussion (time consuming) Articles (could easily be less interesting!)</td>
<td></td>
<td>Videos</td>
</tr>
<tr>
<td>P20 (AF)</td>
<td>-</td>
<td>Articles</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Quizzes</td>
</tr>
<tr>
<td>P21 (EE)</td>
<td>Quizzes (reminded me of tests, am there to learn, not tested!)</td>
<td></td>
<td>Videos</td>
</tr>
<tr>
<td>P22 (SA)</td>
<td>Articles (No need to include in MOOCs, boring, if really needed then give specific bullet point and visuals)</td>
<td></td>
<td>Videos</td>
</tr>
<tr>
<td></td>
<td>Q1A: Why attended?</td>
<td>Q1B: Least favourite part in this MOOC</td>
<td>Q1C: Most favourite part in this MOOC</td>
</tr>
<tr>
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<td>--------------------------------------</td>
<td>--------------------------------------</td>
</tr>
<tr>
<td>P1 (LA)</td>
<td>Professional development + Academic development</td>
<td>Lack of instructors’ involvement / support / engagement in course discussions.</td>
<td>Collaborative activity in hybrid learning environment (MOOC used in hybrid f2f)</td>
</tr>
<tr>
<td>P2 (SA)</td>
<td>Professional development</td>
<td>Lack of engagement from both sides, need better assessment methods (graded, pass/fail)</td>
<td>Openness, accessibility, clarity of content</td>
</tr>
<tr>
<td>P3 (AS)</td>
<td>Professional development</td>
<td>Discussion steps (feel weird)</td>
<td>Subtitles provided with videos</td>
</tr>
<tr>
<td>P4 (SA)</td>
<td>Professional development + personal interest</td>
<td>Discussion steps (are not necessary)</td>
<td>No deadlines, self-paced learning</td>
</tr>
<tr>
<td>P5 (AS)</td>
<td>Personal interest + hobby</td>
<td>Time restriction (short expiry date), Lack of instructors’ involvement/engagement in course</td>
<td>Intrinsic interactivity in course content, possibility of engagement</td>
</tr>
<tr>
<td>P6 (SA)</td>
<td>Professional development</td>
<td>another part of the course where they interviewed individuals; it was useless</td>
<td>One part of the course where they interviewed individuals; it was useful</td>
</tr>
<tr>
<td>P7 (ME)</td>
<td>Academic development</td>
<td>Bad video quality</td>
<td>Course structure; well-structured course</td>
</tr>
<tr>
<td>P8 (ME)</td>
<td>Professional development</td>
<td>Peer assessment, wanted someone more knowledgeable/expert to assess my work</td>
<td>Videos were short but informative and clear, Good combination of text &amp; videos</td>
</tr>
<tr>
<td>P9 (ME)</td>
<td>Personal interest</td>
<td>Videos were too short, I prefer long lecture like videos, not 3 or 4 min long</td>
<td>Documents (rich articles) and more useful article links within those articles</td>
</tr>
<tr>
<td>P10 (EE)</td>
<td>Personal interest</td>
<td>Lack of instructors’ involvement / support / engagement in course. Lack of presence of Subject matter expert</td>
<td>Couple of articles (not long but succinct, provided with learning objectives)</td>
</tr>
<tr>
<td>P11 (AS)</td>
<td>Academic development</td>
<td>Live support from instructor was unavailable. Software in the course was too technical to understand on my own.</td>
<td>Relevant content</td>
</tr>
<tr>
<td>P12 (AS)</td>
<td>Academic development + personal interest</td>
<td>Fee. Badge was only available after fee where it was advertised as free course</td>
<td>Contributors, Interesting Content as it was generated in different contexts.</td>
</tr>
<tr>
<td>P13 (AS)</td>
<td>Professional development</td>
<td>Some course steps were quite long! (he prefers short steps)</td>
<td>Diversity in learners, diversity in the course</td>
</tr>
<tr>
<td>P14 (SA)</td>
<td>Professional development</td>
<td>Articles or reading parts (boring) especially when reading from browser</td>
<td>Videos (felt like f2f learning)</td>
</tr>
<tr>
<td>P15 (AF)</td>
<td>Professional development + personal interest</td>
<td>-</td>
<td>Interface design, good combination of various types of learning activities</td>
</tr>
<tr>
<td>P16 (GE)</td>
<td>Personal interest</td>
<td>Format and line spacing made it difficult to read, prefers more flexible interface</td>
<td>Some videos were good (normally hate learning from videos)</td>
</tr>
<tr>
<td>P17 (AS)</td>
<td>Professional development</td>
<td>Unstructured comments in discussion</td>
<td>Good combination of text &amp; videos</td>
</tr>
<tr>
<td>P18 (EE)</td>
<td>Personal interest</td>
<td>Some parts of the course like some videos were unnecessarily long</td>
<td>Some parts of the course (on gender in sports), relevant and useful discussion</td>
</tr>
<tr>
<td>P19 (LA)</td>
<td>Academic development</td>
<td>Course had lots of articles, it could use more videos and increased interactivity</td>
<td>Taking quizzes after videos</td>
</tr>
<tr>
<td>P20 (AF)</td>
<td>Professional development + personal interest</td>
<td>Discussion as always had a feeling of catching up with discussions</td>
<td>Course content</td>
</tr>
<tr>
<td>P21 (EE)</td>
<td>Professional development + personal interest</td>
<td>Reading articles</td>
<td>Student centered design, no deadlines, self-pace learning, open-ended but practical weekly assignments were given</td>
</tr>
<tr>
<td>P22 (SA)</td>
<td>Academic development + personal interest</td>
<td>-</td>
<td>Some parts of the course where they explained a certain process, some videos</td>
</tr>
<tr>
<td>P1 (LA)</td>
<td>Follow/Linear</td>
<td>Mainly follow the pathway but it depends why I am taking the MOOC? (skipping the activity = risky. Go forward in linear manner step by step, but sometimes go back to revise or revisit some activity)</td>
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<td>--------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------</td>
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<tr>
<td>P2 (SA)</td>
<td>Both</td>
<td>Follow the pathway = If unfamiliar with content, lack of background knowledge, beginner. Choose and pick = If familiar with content, with intermediate to advance background knowledge.</td>
<td></td>
</tr>
<tr>
<td>P3 (AS)</td>
<td>Follow/Linear</td>
<td>Maximal structure. I follow it as the instructor is designed it. So, I go through step by step. In all courses, I always kind of follow it that way.</td>
<td></td>
</tr>
<tr>
<td>P4 (SA)</td>
<td>Follow/Linear</td>
<td>Always watch the videos first. Follow the list of videos that are recommended by the instructor and follow the pathway designed by the instructors, except for discussions and articles and [other] unnecessary things that are not required to complete the course.</td>
<td></td>
</tr>
<tr>
<td>P5 (AS)</td>
<td>Follow/Linear</td>
<td>Someone has put the effort into take you through a certain way, then it's probably best to stick with that. Left to my own devices, I might be a little bit less organised, especially with these courses that I did appreciate the pace, the direction, and just building on small blocks.</td>
<td></td>
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<tr>
<td>P6 (SA)</td>
<td>Follow/Linear</td>
<td>The course is designed by the experts, they design it from the basic to the advanced level...So it's better to go with the designed course [course design]...[but] if the course is starting from the basic knowledge and I already know that? then I would prefer to go forward to find something in the course instead of following the basic design.</td>
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<tr>
<td>P7 (ME)</td>
<td>Both</td>
<td>Depends on the course (background knowledge and topic/discipline familiarity). Technical course = Follow the design. Social science/Educational science (which I am more familiar with) = Choose my own design. If video-based course, go to the videos directly.</td>
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<tr>
<td>P8 (ME)</td>
<td>Follow/Linear</td>
<td>Like following the predetermined learning pathway. Otherwise, I feel like I missed something. And I feel like if I skip a few exercises or like sessions, I will find it difficult to complete tasks in the following sessions. Don't like skipping sessions or skipping, like exercises. I like going in order.</td>
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<td>ID</td>
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<td>Explanation</td>
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</tr>
<tr>
<td>Quizzes (as I don’t need certificate)</td>
<td><strong>P10 (EE)</strong> Discussion (structure of discussion steps confusing), no presence of instructor/subject matter expert in Discuss</td>
<td>Articles (along with learning objectives)</td>
<td></td>
</tr>
<tr>
<td><strong>P11 (AS)</strong> Videos (when you’re forced to watch a video sometimes, I don’t know, it wasn’t the best video to watch. So even though the topic was really relevant, I didn’t particularly love the videos. So I would have preferred to have read the material first.)</td>
<td>Articles (I didn’t particularly want to watch the video. It was going to take too long to watch the video. So, I just perhaps went straight to read the script or the video which I read much quicker than watching the whole video. And to me, that was a lot easier.)</td>
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<td>Quizzes (Quizzes are too general!)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Participant</td>
<td>Type</td>
<td>Feedback</td>
<td></td>
</tr>
<tr>
<td>-------------</td>
<td>------</td>
<td>----------</td>
<td></td>
</tr>
<tr>
<td>P12 (AS)</td>
<td>Discussion</td>
<td>(I think you are supposed to be on your own in a MOOC so why instructor-led discussion steps?)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Quizzes</td>
<td>(give you a sense of fun)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Videos</td>
<td>(I am a visual learner)</td>
<td></td>
</tr>
<tr>
<td>P13 (AS)</td>
<td>Quizzes</td>
<td>(not dislike, but don’t enjoy them either)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Articles</td>
<td>(Less engaging, not fond of dense reading)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Discussion</td>
<td>(specifically instructor-led discussion, motivating)</td>
<td></td>
</tr>
<tr>
<td>P14 (SA)</td>
<td>Articles</td>
<td>(or other textual material, not enjoyable activity)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Videos</td>
<td></td>
<td></td>
</tr>
<tr>
<td>P15 (AF)</td>
<td>Articles</td>
<td>(not dislike but not particularly enthusiastic about articles)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Videos</td>
<td>(found videos to be quite interactive)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Discussion</td>
<td>(like to see teachers in forums)</td>
<td></td>
</tr>
<tr>
<td>P16 (GE)</td>
<td>Discussion</td>
<td>(feels exposed in MOOCs)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Mixed</td>
<td>(videos if they are not talking-head type which is common, don’t show instructor in vid!)</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>[Later in the interview]...</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Articles</td>
<td>Video can work really well when I'm tired (infotainment!). But generally, for learning, I prefer text.</td>
<td></td>
</tr>
<tr>
<td>P17 (AS)</td>
<td>Discussion</td>
<td>(So many people, so many different views, hard to make any sense, lots of noise)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Videos</td>
<td>(easy to follow), informative and practical</td>
<td></td>
</tr>
<tr>
<td>P18 (EE)</td>
<td>Videos</td>
<td>(In this MOOC b/c they were long and less interactive just like long lecture, prefers short and interactive videos)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Discussion</td>
<td>(especially liked reflective part of discussions)</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>[Later in the interview] I prefer video or visuals, because I found them more engaging</td>
<td></td>
</tr>
<tr>
<td>P19 (LA)</td>
<td>Discussion</td>
<td>(time consuming)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Articles</td>
<td>(could easily be less interesting!)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Videos</td>
<td>(Videos followed by Quizzes gives a sense of interactivity, increases engagement)</td>
<td></td>
</tr>
<tr>
<td>P20 (AF)</td>
<td>-</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Articles</td>
<td>(article + visual, reads video transcript)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Quizzes</td>
<td></td>
<td></td>
</tr>
<tr>
<td>P21 (EE)</td>
<td>Quizzes</td>
<td>(reminded me of tests, am there to learn, not tested!)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Videos</td>
<td>(useful, they are short yet informative)</td>
<td></td>
</tr>
<tr>
<td>P22 (SA)</td>
<td>Articles</td>
<td>(No need to include in MOOCs, boring, if really needed then give specific bullet point and visuals)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Videos</td>
<td>(interesting, learn fast from videos)</td>
<td></td>
</tr>
</tbody>
</table>
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