Essays on the Design of Inclusive Learning in Massive Open Online Courses, and Implications for Educational Futures

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Declaration

This thesis is the result of my own work and includes nothing which is the outcome of work done in collaboration except as declared in the Preface and specified in the text. I further state that no substantial part of my thesis has already been submitted, or, is being concurrently submitted for any such degree, diploma or other qualification at the University of Cambridge or any other University or similar institution except as declared in the Preface and specified in the text.

In accordance with the Faculty of Education guidelines, this thesis does not exceed 80,000 words.

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Abstract

This thesis examines the tensions and contradictions of Massive Open Online Courses (MOOCs) as a force for more inclusive tertiary education, particularly for adults without a college degree in the United States. Through a multimethodological research approach yielding three discrete papers, presented as chapters, this work seeks to augment and clarify the existing MOOCs literature across conceptual, quantitative, and qualitative domains. The first paper develops a conceptual framework, 'hegemonic design bias,' that describes the socio-technical development ecosystem in which MOOCs are embedded. This framework helps account for why MOOCs have yet to serve as a democratising force in education by highlighting the processes and constraints that bias MOOC production toward the already well-educated. The potential economic implications of these developments are also considered. The second paper provides insight into how underrepresented learners are engaging with entry-level MOOCs. The exploration of learning analytic data from an initial sample of more than 260,000 enrolees through cluster analysis and multinomial logistic regression indicates that students without a college degree are more likely to be high-performing learners compared to college-educated students in these courses. Additionally, students from approximated lower socioeconomic backgrounds are no less likely to be successful than students from approximated middle and higher socioeconomic backgrounds in these courses. The third paper provides insight into the opportunities and challenges producers face in building inclusive MOOCs through a qualitative analysis of six semi-structured interviews. The interviews unearthed diverse conceptions of inclusion among producers that reflect a sincere normative commitment to make inclusive MOOCs, though the conceptions were quite distinct and fragmented. Producers were intentional about utilising best-practice pedagogy, as well as innovative program design, to include diverse learners. Innovative technology partners helped create interactive, unique experiences, but this also led to challenges in harmonising the design process and required the considerable influence of intermediary actors. To conclude, I briefly consider the implications of these findings for research, practice, and policy, with particular attention to how the public and social sectors can incentivise improved design of MOOCs with the specific intent of helping adults without college degrees develop human capital in order to remain economically resilient amidst the disruptions of skills-biased technological change.

Dedication

To Tim Horley, John Glavin, and Matt Carnes, for lighting the spark.

To Ricardo Sabates and Tom Fikes, for guiding the way.

To my students at Isaac Middle School, for teaching me how to teach.

To my mom, for teaching me how to learn.

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Ad maiorem Dei gloriam inque hominum salutem

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All people have their own model of reality, defined by a line of best fit to the various data points they have encountered in life plus whatever theory they have come across that helps them interpret a story to make sense of that line and that data. My life is no different. There are far too many people to acknowledge that have provided interesting data points and theories to help me interpret reality. A number of these people have been particularly influential during the past four years that I would like to mention specifically.

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Dissemination

Escobari, M., Seyal, I., & **Meaney, M. J.** (2019). Realism about Reskilling: Pathways to Prosperity for Low-wage Workers. The Brookings Institution, Centre for Universal Education.

Meaney, M. J. & Fikes, T. (2019, March). Early-adopter Iteration Bias and Research-praxis Bias in Virtual Learning Environments. *Companion Proceedings of the International Conference on Learning Analytics and Knowledge*, Tempe, Arizona (LAK'19).

Meaney, M. (2018). "The Future of Social Mobility? MOOCs and Hegemonic Design Bias." Oxford Conference on Comparative and International Education, University of Oxford; Faculty of Education Working Papers Series, University of Cambridge.

Meaney, M. J., & Smith, J. V. (2016). Lifelong Learning in 2040. The Roosevelt Institute, The Next American Economy Learning Series.

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1 INTRODUCTION AND OVERVIEW

While information progresses inexorably toward democratisation, knowledge will not, because learning has not; for knowledge to be democratised, so too must learning.
– Unattributed

1.1 Chapter Overview

This thesis examines the tensions and contradictions of Massive Open Online Courses (MOOCs) and similar virtual learning experiences as a force for more inclusive tertiary education aimed at widening participation of traditionally underrepresented groups in the United States (USA). This first chapter details a summary of and roadmap to the subsequent six chapters, providing an overview of the scope of work, research questions, methods, and contributions of this thesis.

Section 1.2 introduces the animating issues from the MOOC literature guiding my investigations. **Section 1.3** details my central research questions and methodological approach. **Section 1.4** describes the three academic papers, presented as chapters, which form the substantive core of this thesis. **Section 1.5** details how these contributions augment the existing MOOC literature. **Section 1.6** clarifies several important definitions and addresses an important issue of voice. **Section 1.7** details the remaining organisation and structure of this thesis.

1.2 MOOCs: Hype and Reality

For at least a decade, MOOCs have generated excitement, optimism, disillusionment, and criticism, from academia and the media alike (Littlejohn and Hood, 2018; Liyanagunawardena, Adams, and Williams, 2013). They remain a nascent and rapidly growing phenomenon likely to affect global education for years to come. When MOOCs first made headlines in 2011 and 2012, they were heralded as a disruptive force that would reduce costs and improve access to education for traditionally underrepresented learners in the USA and around the world (Hollands and Tirthali, 2014a; Daniel, 2012). Characterised by open and free enrolment, eliminating traditional barriers to entry to universities, MOOCs were expected to help democratise higher education (Hansen and Reich, 2015; Literat, 2015; Glance, Forsey, and Riley, 2013). Like many technological developments in education before them (Gouseti, 2010), the reality of MOOCs turned out to be more complex.

The MOOC numbers are impressive. More than 180 million students have enrolled (Shah, 2020). Over 950 universities produce more than 16,300 MOOCs, completion of which can lead to more than 1,000 'MicroCredentials' and more than 60 degrees; the largest MOOC platforms are generating hundreds of millions of dollars, and one plans to go public in 2021 (Shah, 2020). Some applications of MOOCs have, indeed, provided access to learners who otherwise might not have opportunities to pursue tertiary education. This includes underrepresented students seeking to improve their careers or earn college credit (Dillahunt, Wang, and Teasley, 2014), as well as refugees with no access to formal education (Colucci et al., 2017).

From their inception, however, MOOCs have primarily served people from advantaged educational backgrounds (Van de Oudeweetering and Agirdag, 2018; Ho et al., 2015; Emanuel, 2013). This prompted concern that, contrary to the original narrative, MOOCs may be reproducing and reifying, rather than reducing, existing educational inequalities (Adam, 2019; Rohs and Ganz, 2015; Liyanagunawardena, Williams, and Adams, 2014). Having struggled to fulfil its original mission, the MOOC movement may be pivoting to explicitly serve already well-educated professionals (Reich and Ruipérez-Valiente, 2019; Lohr, 2016).

Questions regarding whether MOOCs can provide inclusive learning experiences became even more salient as the COVID-19 pandemic of 2020 forced schools across the USA and around the world to shut down (Bozkurt et al., 2020). Millions of students shifted their learning online. Concurrently, millions of jobs were lost, likely permanently, particularly in lower- and middle-skill elementary and service occupations, amplifying existing labour market polarisation and exacerbating trends of economic inequality (Barrero, Bloom, and Davis, 2020; Autor and Reynolds, 2020). These trends further underscore the need for more inclusive, flexible learning infrastructure for the non-tertiary educated adult workforce.

1.3 Research Questions and Methodological Approach

The purpose of this thesis is to contribute in a practical way to our existing understanding as to why MOOCs struggled to meet their original aim to help democratise learning, and to explore unique data sets, one quantitative and one qualitative, that can provide insight into how this aim might be re-approached moving forward. The following three research questions, further specified and clarified in **Section 3.2**, guided the thesis:

- **RQ1: What dynamics of the educational technology production ecosystem enable or constrain institutions of higher education in the provision of MOOCs and similar virtual learning experiences for underrepresented learners?**
- **RQ2: How are traditionally underrepresented learners engaging with MOOCs and similar virtual learning experiences?**
- **RQ3: What pedagogical and technology design strategies are useful to employ in attempting to build inclusive MOOCs and similar virtual learning experiences?**

Pursuing answers to these questions was not straightforward. Like many topics in educational research, MOOCs are trapped in webs of methodological complexity and disciplinary diversity, undergirded by ontological and epistemological heterodoxy (Raffaghelli, Cucchiara, and Persico, 2015). Because MOOCs are still relatively new and the research regarding them remains emergent, I utilised a multimethodological research design (Hunter and Brewer, 2015), informed by a post-positivist (Phillips, 1990), subtle realist ontology (Hammersley, 1992), seeking to produce socially useful knowledge (Feilzer, 2010). This approach allows me to interrogate critically yet scientifically, accepting the limits of and inherent biases endemic to social scientific inquiry, while also maintaining a fundamental belief in reality despite our imperfect access to it. Further, it allows me to conduct both quantitative and qualitative empirical work, as well as generative, theory-building work.

The genesis of the research questions, and how they were further specified and operationalised, as well as the ontological and research design orientations, are discussed more fully in **Chapter 2**. Building from the research design articulated in **Chapter 2**, **Chapter 3** provides an outline of the specific research questions and sub-questions examined and methods used in the substantive core of the thesis. Additionally, I discuss the context of the research conducted, the ethical issues considered and how these were dealt with, as well as the limitations of these research approaches.

1.4 Substantive Core: Conceptual, Quantitative, and Qualitative Papers

Chapter 4 through **Chapter 6** present three discrete papers that seek to augment and clarify the existing literature across conceptual, quantitative, and qualitative domains. These papers include the development of a conceptual framework called 'hegemonic design bias,' the exploration of MOOC data from an initial data set of more than 260,000 enrolees through descriptive statistics, cluster analysis, and multinomial logistic regression, and qualitative analysis of six semi-structured interviews with MOOC producers. These studies are unified by a focus on whether and how MOOCs are serving traditionally underrepresented learners. These contributions are presented as chapters, each containing its own literature review and methods sections.

In **Chapter 4**, 'hegemonic design bias' describes a series of processes and constraints that optimise MOOC production in a manner biased toward the well-educated. The framework considers the macro, meso, and micro levels operative in distance education (Zawacki-Richter, 2009) and is informed by socio-technical interaction network theory (Meyer, 2006), giving primacy to neither technical nor social factors. Through a critical synthesis of the literature, as well as conceptual development of my own, I identify several institutional and cultural factors endemic to higher education, biases embedded in production systems of MOOCs, and shortcomings in the design of MOOCs themselves that combine to produce and reinforce the skewness of MOOC design toward the educationally advantaged. By situating MOOCs in the context of skills-biased technology change in the labour market, hegemonic design bias suggests that the rise of MOOCs coincides with an increasingly technologised economy, where returns to education are accelerating, the gains from which are increasingly captured by a concentrated, socioeconomically advantaged elite. Considerations for how to operationalise hegemonic design bias as a series of hypotheses are presented in conclusion. Hegemonic design bias was identified concurrent to the execution of the empirical chapters, so these hypotheses were not tested explicitly.

In **Chapter 5**, I leverage a common method of computationally intensive data analysis on previously unexamined data from entry-level MOOCs produced by a major research university in the USA. Understanding the behaviour patterns of MOOC users is central to the academic literature (Li and Baker, 2018; Ferguson et al., 2015; Kizilcec et al., 2013). Myriad analytic methods have been used to understand different behaviour patterns of student subgroups using MOOCs (Gardener and Brooks, 2018; Kizilcec and Brooks, 2017). Less attention has been paid to considering whether and how these behavioural subgroups are differentiated by demographic characteristics, particularly characteristics revealing dimensions of underrepresented status like educational and socioeconomic background.

From an initial sample of more than 260,000 learners, I cluster analyse a subset of data from more than 29,000 participants who submitted an assignment for a grade in one of nine entry-level MOOCs. Manhattan Distance (Loohach and Garg, 2012) and Gower Distance (Gower, 1971) measures are computed based on engagement and achievement data, and clusters are derived from application of the CLARA and PAM algorithms (Schubert and Rousseeuw, 2019). The clusters are enriched by demographic data, with a particular focus on education level, as well as by approximated socioeconomic status (SES) derived from the American Community Survey.

In **Chapter 6**, I detail thematic analysis derived from semi-structured interviews conducted with a set of producers that helped design the entry-level MOOCs analysed in **Chapter 5**. Leveraging methods commonly used in qualitative MOOC literature (Lowenthal, Snelson, and Perkins, 2018; Iniesto, McAndrew, Minocha, and Coughlan 2016), the interviews seek to explore how these producers are considering traditionally underrepresented students and the challenges these students face when designing MOOCs. Academic staff, Instructional Designers, and Program Managers are interviewed in order to collect insights from the constellation of university producers contributing to the construction of these courses. The interviews probe how the mindsets, design processes, and practices of these producers take into consideration what underrepresented learners may need to be successful.

1.5 Conclusions and Contributions of this Thesis

Taken together, these papers aim to provide several important insights to the MOOCs literature. **Chapter 4** on hegemonic design bias utilises an existing base of transdisciplinary research to explore why MOOCs have struggled to democratise education and seeks to do so in a constructive way by developing a detailed conceptual framework of the processes and constraints that optimise MOOC production toward the educationally advantaged. Furthermore, hegemonic design bias adds an important frame to the debate around MOOCs by situating them in the context of skills-biased technology change in the labour market. Hegemonic design bias was pursued, in part, because, as other scholars have noted, much research falls into the trap of either describing reality, or complaining about it (Wegerif, 2018; 2013). This tendency in the MOOCs literature has left the field robust and productive yet cloistered and disciplinarily self-referential, with conceptual work often neglecting to articulate its ontological and methodological orientation, and, reciprocally, empirical work remaining detached from comprehensive, detailed conceptual frameworks or theory (Bozkurt, Akgün-Özbek, and

Zawacki-Richter, 2017; Raffaghelli et al., 2015). Hegemonic design bias provides a framework for future research to bridge disciplinary and methodological domains, and helps re-centre the MOOC debate on underrepresented learners.

Researchers have called upon the field to examine the specific engagement patterns of underrepresented learners using MOOCs (Gardner and Brooks, 2018; Joksimović et al., 2018; Deng, Benckendorff, and Gannaway, 2017). **Chapter 5** provides insight into how underrepresented learners are engaging with entry-level MOOCs. Results indicate that, in the courses analysed, learners without a college degree are more likely to be high-performing compared to college-educated learners; additionally, learners from approximated lower socioeconomic backgrounds are no less likely to be successful than learners from approximated middle and higher socioeconomic backgrounds in the USA. These findings are noteworthy insofar as they indicate that, while MOOCs have struggled to democratise learning broadly speaking, there are possibilities for more inclusive outcomes.

Several papers have called for more investigation into the actors producing MOOCs and their design processes (Zhu, Sari, and Lee, 2018a; Veletsianos and Shepherdson, 2016; Gašević, Kovanović, Joksimović, and Siemens, 2014) . **Chapter 6** yields a number of observations about the opportunities and challenges producers face in building inclusive MOOCs. First, diverse conceptions among of inclusion among producers reflect a sincere normative commitment to make inclusive MOOCs, though the conceptions were quite distinct and fragmented. Second, producers were intentional about utilising best-practice pedagogical methods, as well as innovative program design, in an attempt to include many kinds of learners. Finally, technology partners helped create interactive, unique experiences, but this also led to challenges in harmonising the design process and enabled the considerable influence of 'third-space producers' (White and White, 2016).

To conclude, I reflect on recent developments of the MOOC debate and the extent to which this thesis challenges some of the underlying assumptions of these developments; particularly, the pivot many MOOC platform providers and universities seem to be making to serve as continuing education resources for corporations and workers looking to upskill, without particular attention to the backgrounds of learners (Reich and Ruipérez-Valiente, 2019). This pivot marks a sharp departure from the initial democratising discourse surrounding MOOCs; furthermore, the pivot may be premature, as provisional evidence from this thesis, as well as other academic research, suggests that specific MOOCs designed and constructed in intentionally inclusive ways may serve segments of traditionally underrepresented students reasonably well. Building on work I completed as a Visiting Scholar at the Brookings Institution, I consider how the public and social sectors can incentivise improved design of MOOCs with the specific intent of improving the development of human capital for adults without a tertiary degree in an inclusive way. These designs can help ameliorate the challenges associated with economic disruption resultant from skills-biased technology change (Escobari, Seyal, and Meaney, 2019).

1.6 On Definitions and Voice

A few terms used regularly in this thesis are contested and require specific definition.

1.6.1 MOOCs

The first term to define is **MOOCs**, or Massive Open Online Courses. **Section 2.2** briefly considers the historical development of the MOOC, the more open educational origins of cMOOCs (Connectivist MOOCs), the more corporate origins of the xMOOCs (Extension MOOCs), and some of the complexities of more recent iterations as they relate to the notion of 'openness.' A narrower conception of 'openness,' for example, stipulates all content in a MOOC should be freely available online, for the duration of a course and afterward (Major and Blackmon, 2016). A broader interpretation, and the one utilised in this thesis, defines 'openness' as being free to access and requiring no formal admission procedures (Deng, Benckendorff, and Gannaway, 2019). **MOOCs** then, are defined as:

> …open, large-scale web-based courses designed and delivered by accredited higher education institutions and organisations in which anyone with a smart device and internet connection can participate, regardless of age, gender, geographic location, or education background… However, while the content and learning activities are free to access, some of the MOOCs may charge a small fee to issue a 'completion certificate.' (Deng et al., 2019, p. 48)

This definition encompasses the xMOOCs provided by the two major American MOOC providers, Cousera and edX. These types of MOOCs, and similar virtual learning experiences (that may no longer call themselves MOOCs but share similar properties), are the focus of my thesis.

Focusing on Coursera- and edX-style MOOCs does exclude several other noteworthy MOOC experiments. FutureLearn, the U.K.-based MOOC provider affiliated with the Open University, and Swayam, an Indian MOOC provider, served some 30 million students in 2020 (Shah, 2020). Additionally, it is estimated that some 52,000 Chinese language MOOCs are available across two dozen Chinese MOOC platforms (Ma, 2021). In short, there are thousands of MOOCs serving millions of students that are not necessarily produced in the USA nor using the English language.

For the purposes of this thesis, however, a focus on Coursera and edX-style is appropriate for two reasons. First, the MOOC data I analyse in Chapter 5, and the MOOC producers I interview in Chapter 6, are situated in the context of a research-intensive university in the USA utilising the edX platform. And second, Coursera and edX remain the dominant MOOC providers. Of the more than 180 million enrolled learners in 2020, 111 million enrolled in a Coursera or edX MOOC (Shah, 2020). Additionally, while the scope and potential scale of the Chinese MOOC landscape is of serious interest, the data regarding these platforms is often unavailable, unreliable, or difficult to validate (Shah, 2020).

1.6.2 Democratise

Democratise in this thesis refers to the expansion of educational opportunity, in terms of providing access to more learners and that those learners can engage effectively (Littlejohn and Hood, 2018). This usage of democratise is aligned with common conceptualisations in the MOOCs literature (Reich and Ruipérez-Valiente, 2019; Rohs and Ganz, 2015; Dillahunt et al., 2014), as well as how Coursera (Lewin, 2012) and edX (Agarwal, 2013) originally framed their mission. While MOOCs have undergone several important iterations discussed more fully in **Section 2.2**, the aim of providing universal access to high-quality learning remains the central mission of these two companies, as described on their website today. The homepage of Coursera.com reads, “World-class learning for anyone, anywhere” (Coursera, 2021). The “about” page on edX.org states their mission to be, “Increase access to high-quality education for everyone, everywhere” (edX, 2021).

The word democratise has a long history in the context of education, leaving an indelible imprint of meaning beyond the conceptualisation of access referenced in this thesis. This other definition describes education as a process of no less than the self-directed development of individual flourishing.

John Dewey famously wrote that, “To subject mind to an outside and ready-made material is a denial of the ideal of democracy, which roots itself ultimately in the principle of moral, self-directing individuality” (p. 199). This definition of democratise has important implications in the MOOC debate as well, notably in that MOOCs enable learners to engage with learning as they see fit, non-linearly and without constraint of a pre-specified course framework (Littlejohn and Hood, 2018). Additionally, Milligan, Littlejohn, and Margaryan (2013) detail the significance of knowledge and content co-creation among learners in connectivist cMOOCs, communicative co-creation being a central tenet of Deweyan pedagogy (Hansen, 2012). Beyond these conceptualisations of democratise, it is important to note that producers of MOOCs may also pursue such ventures for other reasons. Universities may pursue the development of MOOCs to enhance prestige or further build capacity for the creation of virtual learning environments more broadly to better prepare for the digitisation of higher education (White, Davis, Dickens, León, and Sánchez-Vera, 2014).

These alternative definitions of democratise and potential motivations for producing MOOCs, while important to investigate and consider, are beyond the scope of this thesis. Instead, the focus is squarely on Cousera- and edX-style xMOOCs, originally conceptualised to broaden access to high-quality learning for underrepresented learners.

1.6.3 Underrepresented Learners

The next term to define is underrepresented learners**.** Underrepresented learners are defined as a) adults without a tertiary education b) adults from lower socioeconomic backgrounds, or c) adults who are both from lower socioeconomic backgrounds and without a tertiary degree.

MOOCs have disproportionately served learners who already have a tertiary degree (Reich and Ruipérez-Valiente, 2019). As is defined further in hegemonic design bias, skills-biased technology change is most disruptive to the economic prospects of people without a tertiary degree, for whom open, flexible learning infrastructure will become increasingly important to acquire new skills.

Additionally, MOOCs enrol learners from higher socioeconomic backgrounds (Ganeline and Chuang, 2019; Hansen and Reich, 2015). The American Psychological Association (APA) defines socioeconomic status (SES) as:

> …not just income but also educational attainment, financial security, and subjective perceptions of social status and social class. Socioeconomic status can encompass quality of life attributes as well as the opportunities and privileges afforded to people within society. (APA, 2021)

Research has consistently demonstrated a link between lower SES status and lower rates of academic progress and achievement. According to the United States' National Center for Education Statistics (NCES), in the USA:

> A smaller percentage of students of low socioeconomic status (SES) than students of middle SES attained a bachelor's or higher degree within 8 years of high school completion (14 vs. 29 percent), and percentages for both groups were smaller than the percentage of high-SES students who attained this level of education (60 percent). (NCES, 2015)

Learners with lower educational backgrounds, particularly those without tertiary education, as well as those who have experienced deprivation of other material, socio-cultural, and economic resources, are likely to have distinct learning needs and abilities in the context of digital learning environments (Warschauer and Matuchniak, 2010) .

In **Chapter 4**, which describes hegemonic design bias, underrepresented is operationalised specifically to mean learners without a college degree in the USA. In **Chapter 5**, where cluster analysis is explored, underrepresented is operationalised along both dimensions, learners without a college degree, and learners from low SES backgrounds. In **Chapter 6,** the producer interviews, underrepresented is left undefined, to not unduly influence the data.

1.6.4 Inclusive Design

Section 4.5.2.3, the micro level of hegemonic design bias, will consider more aspects of inclusive design in the context of learning and MOOC production. Inclusive design has its origins in the disability's rights movement, and inclusion in education has a particular association with the movement to ensure the least restrictive learning environments for students with special needs (Kavale and Forness, 2000). Inclusion, accessibility, and universal design all have particular meanings in a variety of contexts in technology design, education, and a variety of other disciplines. I do not wish to inappropriately co-opt any of the specific significances of these terms. Indeed, as a person with a speaking disability who has both benefitted from an increased societal consciousness around difference and suffered from a lack of it, I would be betraying myself to do so.

At the same time, as a former teacher and technologist, I have come to understand inclusive design as a methodology that broadens the focus of inclusion to centre on the needs of any particular group, in line with the definition of the Cambridge Inclusive Design Unit, which states:

> Every design decision has the potential to include or exclude [users]. Inclusive design emphasises the contribution that understanding user diversity makes to informing these decisions, and thus to including as many people as possible. User diversity covers variation in capabilities, needs and aspirations. (Inclusive Design Toolkit, 2021)

And, correspondingly,

> Inclusive design does not suggest that it is always possible (or appropriate) to design one product to address the needs of the entire population. Instead, inclusive design guides an appropriate design response to diversity in the population through:
>
> - Developing a family of products and derivatives to provide the best possible coverage of the population.
> - Ensuring that each individual product has clear and distinct target users.
> - Reducing the level of ability required to use each product, in order to improve the user experience for a broad range of customers, in a variety of situations. (Inclusive Design Toolkit, 2021)

I am particularly interested in understanding whether and how dimensions of being underrepresented have been considered during the design process of MOOCs; specifically, whether and how the needs of users without a tertiary education, or from a lower SES background, have been considered. This is especially relevant given the numerous accounts of researchers assessing MOOC design and pedagogy as being particularly behaviourist (Bates, 2019) and requiring a high degree of self-regulation skills (Littlejohn, Hood, Milligan, and Mustain, 2016), features likely to impose barriers to underrepresented students. These questions are investigated in **Chapter 6**, the qualitative interviews.

1.6.5 Repetition

Further defined in **Section 2.6**, this thesis is presented as a multimethod project of three discrete papers, each with their own introductions, literature reviews, methodologies, results, conclusions, and limitations sections. These are all distinct. Some of the cited literature will overlap, in some cases considerably, as well as general comments included to frame issues.

1.6.6 First Person

I use the first person singular periodically throughout this thesis, especially when describing components of my PhD journey, and when describing the methodological treatment of data.

As further defined in **Section 2.5**, and in accordance with a post-positivist (Phillips, 1990), subtle realist (Hammersley, 1992) ontological and epistemological approach to social science, I recognise the product of this research effort is inseparable from my own worldview, interpretive lens, and biases (Hammersley, 1992). Furthermore, I prefer the active to the passive voice, as it tends to make writing clearer. Finally, alternatives, such as 'the researcher,' can produce more confusion than clarity, especially given the volume of other research referenced, completed by several other researchers (Carter, 2008).

1.7 Outline of Thesis

The remainder of this thesis is organised as follows:

- **Chapter 2.** To Describe Reality, or to Complain about It? A Critical Review of MOOC Research, and Ontological Considerations.
- **Chapter 3.** Research Questions and Methods, Context, Ethics, and Limitations.
- **Chapter 4.** Hegemonic Design Bias: A Conceptual Exploration of Why MOOCs Struggle to Democratise Learning.
- **Chapter 5.** Adding a Demographic Lens to Cluster Analysis of Participants in Entry-level MOOCs.
- **Chapter 6.** Building Inclusive, Entry-level MOOCs: Perspectives from Producers.
- **Chapter 7.** Toward More inclusive MOOC Design: Primary Conclusions and Limitations, Areas for Future Research, and Practice and Policy Applications.

2 TO DESCRIBE REALITY, OR TO COMPLAIN ABOUT IT? A CRITICAL REVIEW OF MOOC RESEARCH, AND ONTOLOGICAL CONSIDERATIONS

We routinely recognise that in most things we can never know anything for sure. But this does not mean that we know nothing.
– Martyn Hammersley (1995a, p. 62)

2.1 Outline of the Chapter

Section 2.2 describes the genesis of my research questions. **Section 2.3** critically reviews the MOOC literature by examining existing systematic literature reviews of MOOC research to identify key themes and trends. **Section 2.4** explores the key themes and trends identified, with a particular focus on what the literature suggests regarding underrepresented learners in MOOCs, as well as the methods and philosophical underpinnings of that research. **Section 2.5** explicitly considers the dominant discourses in the research literature regarding MOOCs and underrepresented students, one critical and one more in the line of traditional social science. I then consider the relative merits of the traditional social science approach, underpinned by a positivist ontology, and the limits of this philosophical framing. Post-positivism and subtle realism are presented as ontological frameworks that capture the incisive critiques of more critical discourses while maintaining adherence to traditional social science tenets. To conclude, **Section 2.6** synthesises these explorations into a final statement of my specific philosophical approach and research design.

While most of the doctoral research I have examined typically devotes a specific portion of the thesis to these questions, it is usually limited and often framed without much controversy. These are questions, however, that have bedevilled the social sciences for centuries. Explicit consideration and exploration of these questions was an essential part of my doctoral training, contoured my final thesis considerably, and, most importantly, was vital to answering my research questions. Therefore, instead of succinctly stating my assumptions regarding these questions, I work through them in this chapter to justify them more adequately.

2.2 Genesis of Research Questions

How might institutions of higher education provide inclusive tertiary learning opportunities at scale? What pedagogical strategies and technology design paradigms are useful to employ in attempting to do so? These are questions that originally animated the pursuit of my doctoral work. From 2014-2015, I worked as a product manager building on-ramps to digital higher education for non-tertiary educated learners. I consulted the research literature to determine what pedagogical strategies and design paradigms had been developed to help underrepresented learners succeed in digital education contexts. One early conclusion from this search was the extent to which education technology raised questions across a range of fields, including traditional domains like curriculum and instruction, to more adjacent domains like economics, design, and computer science, to more emancipatory domains like critical postmodernism. I also learned that online learning fundamentally transformed higher education. In 2002, less than 50 percent of university leaders in the USA believed that online learning was critical to their institution's long-term strategy; by 2015, that number reached over 70 percent (Allen and Seaman, 2015). From 2012-2013, online student growth represented more than 70 percent of total enrolment growth in higher education (Allen and Seaman, 2015). Formal university online courses are typically reserved for students who have enrolled in either on-campus or online programs. Enrolment in such courses usually poses some barriers to entry, including admissions processes and costs associated with matriculation. In terms of the efficacy of online programs, evidence suggests that online courses can be as effective as face-to-face classes, if well executed (Chirikov, Semenova, Maloshonok, Bettinger, and Kizilcec, 2020; Means, Toyama, Murphy, Bakia, and Jones, 2010), though this is contested, especially as it relates to more vulnerable learners (Xu and Jaggars, 2011). I also discovered that a new entrant, MOOCs, had made significant impact on the field since 2008, when the first MOOC was launched.

2.2.1 MOOCs

David Cormier coined the term MOOC in 2008 to describe an online course designed by George Siemens and Stephen Downes called *Connectivism and Connected Knowledge,* offered at the University of Manitoba (Hollands and Tirthali, 2014a). A total of 25 students took the class as a credit-bearing course for a fee, while an additional 2,300 participated as 'open' students. The Siemens and Downs course was a cMOOC, or 'connectivist' MOOC, and was guided by a pedagogical philosophy coined by Siemens called 'connectivism.' cMOOCs sought to curate learning experiences through social interaction with peers, with the teacher as a component part of the experience, but not the central focus. Students would build upon each other's academic work and progress in academic understanding and competence as a community. cMOOCs also typically withstand the narrower definition of 'open' to be comprised of resources that are open access and reusable (Hollands and Tirthali, 2014a).

The relative merits of 'connectivism' as a new learning theory are disputed. It is new, is conceptually underdeveloped, and problematic to the extent that it is (or is not) different from social constructivism (Clará and Barberá, 2014). Furthermore, while more democratic in their original conception and orientation, cMOOCs have been criticised as producing unstructured floods of information (Liyanagunawardena et al., 2014), a learning environment particularly unfriendly to the educationally disadvantaged, as critical literacy, learning autonomy, and learner presence are all required (Koutropoulos and Zaharias, 2015). That said, these MOOCs are much more aligned to the traditional Open Education Movement, compared to the xMOOC, which arrived shortly after.

The necessity of scaling to millions of learners required new computer infrastructure for learning, which helped draw the attention of elite universities and Silicon Valley. Coursera was launched by Daphne Koller and Andrew Ng, Professors at Stanford, Udacity was launched by Stanford Professor Sebastian Thrun, and edX was launched by Harvard and the Massachusetts Institute of Technology (MIT) (Weller, 2015; 2014). These entities produced what would come to be known as xMOOCs. The 'x' connotes 'extension,' as in MITx or Harvardx. xMOOCs involve a sequenced delivery of content in a structured manner, and there is less emphasis on participants co-creating. When the New York Times named 2012 the "year of the MOOC" (Pappano, 2012), it was xMOOCs they were referring to; Coursera, edX, Udacity, and the other companies generating hype and 'disrupting' American higher education are in the business of producing xMOOCs.

MOOCs were an attractive research topic for several reasons. MOOCs are characterised by open and free enrolment, and were widely expected to have a significant democratising effect on higher education (Hansen and Reich, 2015; Literat, 2015). Unlike formal university online programs, MOOCs have no barriers to entry in terms of cost or admissions processes (Glance et al., 2013). MOOC platforms were growing at an incredible pace (Shah, 2016), and they enrolled millions of students, all of whom would leave detailed user data which could be mined to understand engagement patterns in a setting similar to a massive research laboratory (Diver and Martinez, 2015).

At the same time, MOOCs seemed to be delivering underwhelming outcomes. A report by MIT and Harvard found that of the over three million students who signed up for an edX MOOC from 2012-2014, 43 percent never began the course (Ho et al., 2015). While MOOCs provided free and open access to content, open access alone was not sufficient for students to follow through with course completion. Roughly 65 percent of MOOC students already held a bachelor's degree and less than ten percent obtained a certified credential after the course (Ho et al., 2015). This presented a portrait far different from the democratic image of MOOCs providing access to high-quality education content to high proportions of those previously excluded from higher education. This result has been observed repeatedly in the research literature (Meaney and Fikes, 2019; Van de Oudeweetering and Agirdag, 2018; Rohs and Ganz, 2015).

These outcomes prompted criticism and led some observers to declare MOOCs dead, though this was also likely hyperbolic (Naidu, 2020). This trend of over-inflated expectations followed by a harsh reality check is a common phenomenon for new products, characterised as the 'hype cycle,' depicted in **Figure 2.1** (Bozkurt, Keskin, and de Waard, 2016).

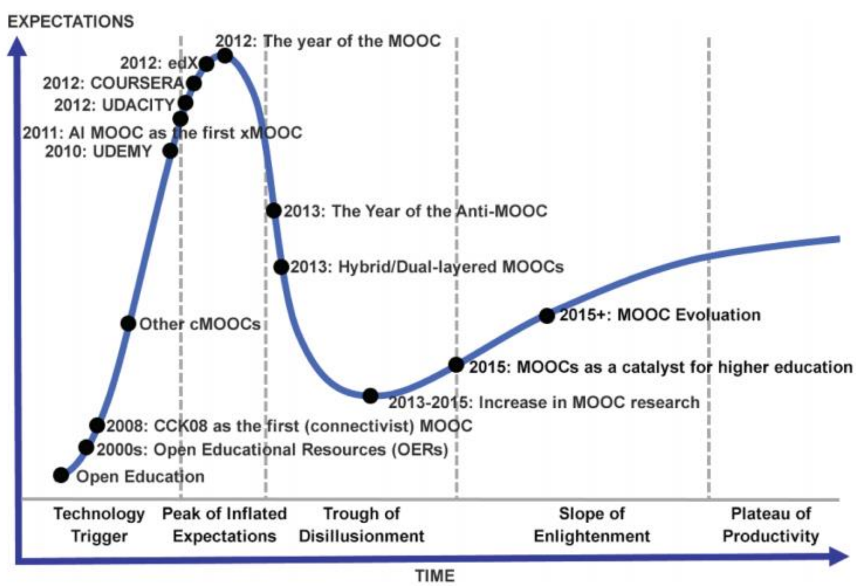


Figure 2.1: Gartner Hype Cycle of MOOC developments. From Bozkurt et al., 2016.

Different versions of MOOCs were considered. These variations included SPOCs, or Small, Private, Online Courses, with enrolment limits and barriers, like admissions essays; POOCs, which were Participatory Open Online Courses and geared toward improving engagement; LOOCs, Little Open Online Courses, predominantly for students enrolled in a formal program but with open seats for a limited number of learners; and SMOCs, or Synchronous Massive Online Courses, which could host up to 10,000 students and were open entry and available for credit. There were also mini-MOOCs, HOOCs, BOOCs, and VOOCs, and others. Many of these efforts were aimed at ameliorating the attrition and achievement problems, sometimes imposing more barriers to enrolment (Pilli and Admiraal, 2016).

Many major MOOC providers evolved as well. Udacity, for example, shifted to become a training provider for high-skill jobs, offering Nanodegrees (Lohr, 2016). Similarly, edX began to offer Professional Certificates and Coursera started to offer Specialisations. These courses maintain open enrolment, and charge a fee if students wish to convert successful course completion into a non-degree credential (Hollands, 2017). Some authors have termed this a ‘microcredentialing craze’ (Ralston, 2021), while the CEO of edX maintains that evolving the business model is required to eventually have more impact (Shaw, 2019). While many of these offerings are aimed at highly educated working professionals, edX and Coursera still provide substantial content at the baccalaureate level.

The focus of this thesis is the Coursera- or edX-style xMOOC and similar virtual learning experiences that may no longer brand themselves as MOOCs but have the same features. These courses retain the following properties, in alignment with the definition from Deng et al. (2019):

- Open enrolment without entry qualifications, and have no barriers to access content (though the content may be copyrighted and thus not meet the ‘open’ definition of OER)
- Online, and available to anybody with an internet connection
- Free to complete
- May charge a fee for certification.

These were the courses that originally sparked my interest in MOOCs and guided the literature review in this chapter. Furthermore, Coursera and edX MOOCs continue to be the largest providers of these types of courses in the world, accounting for some 110 million of the 180 million enrolments worldwide (Shah, 2020). Hegemonic design bias, the focus of **Chapter 4**, is focused on the xMOOC; the data analysed in **Chapter 5** comes from courses hosted on edX; and the producers I interviewed for **Chapter 6** worked to build courses hosted on edX.

Focusing on Coursera- and edX-style MOOCs does exclude other MOOC experiments, like FutureLearn, the U.K.-based MOOC provider affiliated with the Open University, and Swayam, and Indian MOOC provider, which served some 30 million students in 2020 (Shah, 2020). Additionally, some 52,000 Chinese language MOOCs are available across two dozen Chinese MOOC platforms (Ma, 2021). These MOOCs, neither produced in the USA nor using the English language, are serving millions of learners. Nevertheless, because of my focus on xMOOCs in hegemonic design bias, the continued dominance of Coursera and edX in numbers of learners served (Shah, 2020), and the availability of data from edX for my empirical analyses, specifying my focus on these kinds of MOOCs is prudent.

2.2.2 Why did MOOCs Struggle to Democratise Learning?

Based on my experiences as a teacher and a technologist, I had some initial hypotheses for why MOOCs were struggling to democratise tertiary education, but I knew that the research literature could provide more insights. As is common in doctoral work, my original impressions and intuitions found some support, but were complicated by the various perspectives through which researchers were studying MOOCs (Raffaghelli et al., 2015).

The explosion of learning analytic data attracted interest from myriad disciplines with different methodologies and theoretical orientations, with the disciplines of Educational Data Mining and Learning Analytics rising in prominence. Millions of observations from clickstream data could be analysed to model student engagement and outcomes, offering detailed portraits of technology use and learning (Gardner and Brooks, 2018). Researchers had never been able to observe how many and which students opened a textbook, which students interacted with whom, and who logged on at all (Eynon, Hjoth, Yasseri, and Gillani, 2016). Leveraging this research for practical insights for how to improve course design for underrepresented learners remains an underexplored area in the literature (Littlejohn and Hood, 2018; Deng et al., 2017). Movements in several fields have started to consider the dimensions of fairness and equity in computationally intensive research, with specific interest into how these methods might amplify existing social inequities, notably the Workshop on Fairness, Accountability, and Transparency in Machine Learning, and the Workshop on Fairness and Equity in Learning Analytic Systems (Holstein and Doroudi, 2019). This is a burgeoning area of the MOOC literature, though significantly underdeveloped.

I also encountered a more critical strand of research, with scholars doubting the claim that MOOCs were doing anything new at all (Weller, 2014), to concerns that MOOCs might be exacerbating existing inequalities (Littlejohn and Hood, 2018; Evans and McIntyre, 2016; Liyanagunawardena et al., 2014). Critiques of MOOCs extended beyond educational inequality to concerns regarding privacy and data governance (Prinsloo and Slade, 2015; Slade and Prinsloo, 2013), the neocolonialism of Western knowledge (Adam 2019; Altbach, 2014), and the neoliberal assault on state services (Jones, 2015), among others.

The literature continued to indicate two central themes. First, that MOOCs unleashed a new era of quantified, digital education science that could yield hitherto inaccessible insights into student learning. Second, that while MOOCs were originally wound up in a discourse of educational democratisation, the subsequent empirical basis for this was lacking. Convincing explanations for why this was the case, however, seemed inadequate. Much of the literature fell into the camp of describing reality, or complaining about it (Wegerif, 2018; 2013).

2.3 Reviewing the Literature

While still a relatively recent phenomenon, a trove of academic literature has emerged across a variety of disciplines to analyse MOOCs. Several researchers have sought to examine this body of work through rigorous literature reviews. Bibliographic methods, the methodologies commonly employed to conduct literature reviews, form a distinct type of research methodology requiring specialised training. I am not trained in these methods, and a methodologically rigorous, comprehensive literature review is not part of my thesis. Rather, I conducted a literature review based on convenience and purposive sampling. Grounding my research in the existing literature is essential because, as noted in Bozkurt, et al. (2016), “in order to understand how we should design and develop learning for the future, we must first take stock of what we know…” (p. 206), echoing Siemens, Gašević, and Dawson (2015).

Aras Bozkurt, an Associate Professor at Anadolu University in Turkey, has contributed many highly cited literature reviews to the field. These have been published in the International Review of Research in Open and Distributed Learning (IRRODL), the sixth highest-ranked education technology journal on Google Scholar (2021). In these reviews, Bozkurt commonly cites other major contributions to the field.

This provided guidance to my review and a selection of literature reviews to evaluate and include. I was particularly mindful to include reviews that commented on what the MOOC literature revealed about usage by underrepresented students, how the courses were being designed and developed, and what methods researchers employed to reveal this knowledge.

Liyanagunawardena et al. (2013) conducted the first major review of the MOOC literature. The researchers reviewed 45 peer-reviewed papers published between 2008-2012 and described eight emergent areas of interest: “introductory, concept, case studies, educational theory, technology, participant-focused, provider-focused, and other” (p. 202). As the authors note, “the lack of published research on MOOC facilitators’ experience and practices leaves a significant gap in the literature” (p. 217). The authors foreshadow a number of common themes in the MOOC literature: the distinction between the early cMOOC and the xMOOC; the stark dropout rate of students; a focus on the demographics of the participants, when available; the large amount of data that can be used for analysis; a Western bias of the participants and the providers; as well as the importance of motivation as it relates to completion and the possibility of earning college credit. Finally, they note that qualitative analysis of MOOCs was quite limited.

Ebben and Murphy (2014) reviewed 25 peer-reviewed articles published from 2009-2013. They identified two phases of MOOC research. The first phase, between 2009-2012, centred on the cMOOC, “emphasized human agency, user participation, and creativity through a dynamic network of connections afforded by online technology” (p. 333). This phase focused on the development of connectivism as a learning theory and experimentation in early cMOOCs. Phase two, from 2012-2013, focused on the xMOOC. This phase featured the development of a focus on Learning Analytics, or “the set of practices that collect and use statistically based data to identify patterns for understanding learning behaviours and outcomes” (p. 337). Ebben and Murphy also noted the development of a critical discourse that identified issues of epistemology, pedagogy, and cultural hegemony in MOOCs.

Gašević et al. (2014) analysed 266 research proposals submitted to the Gates Foundation-funded MOOC Research Initiative, administered by Athabasca University. Research proposals that were based on learning analytic methods proved to be the most successful. Another implication noted by the researchers was a need to increase efforts toward interdisciplinarity.

Raffagelli et al. (2015) analysed 60 MOOC papers published between 2008-2014, with a particular focus on the methodological approaches. They concluded that the:

> …emerging picture is that of a research field in its infancy, heavily relying on theoretical research and case studies, which is just beginning to identify suitable methods to deal with large cohorts of learners, very large amounts of data and new ways of learning. The state ‐ of ‐ the ‐ art is also quite fragmentary, due to the different epistemological and ontological conceptions of the authors of the papers about the nature of the issues faced and the way they should be studied. (p. 488)

This succinct but vital insight significantly informed my reading of the MOOC literature and my thesis project as a whole.

In 2015, Velestianos and Sheperdson used bibliographic methods on the MOOC literature to study interdisciplinarity in the field. They focused on the empirical literature between 2013-2015. They concluded that xMOOCs were generally criticised for their reliance on behaviouralist pedagogy, as well as that research on xMOOCs spurred a great amount of interdisciplinarity in the empirical literature, which, in part, contrasts with the claim of Gašević et al. (2014).

In 2016, Velestianos and Sheperdson produced another review of the empirical MOOC literature between 2013-2015, this time focused on the "geographic distribution, publication outlets, citations, data collection and analysis methods, and research strands of empirical research focusing on MOOCs during this time period" (p. 198), as opposed to the shifting interdisciplinarity. They found that most MOOCs literature was published by scholars in either North America or Europe, nearly half of the papers were cited zero times, with a few papers widely cited, and that most research took a quantitative approach. They echo Liyanagunawardena et al. (2013), noting a lack of qualitative research. They note two more important findings related to my interests by concluding that there was a lack of research into the producer side of MOOCs, as well as there being inadequate analysis of learner subpopulations, despite the innovations in big data and learning analytics.

Deng et al. (2017) conducted a literature review focused on the teaching and learning aspects of MOOCs. The key dimensions identified through reviewing 95 published papers between 2014 and 2016 were: student characteristics, including demographics and motivations; teaching context; student engagement; and learning outcomes. They note, “The characteristics of non-mainstream consumers of MOOCs, the ways in which they utilise MOOCs, and difficulties they might have are not yet clear. Future research should therefore shed light on these underserved MOOC populations” (Deng et al., 2017, p. 181).

Bozkurt et al. (2017) conducted a review of 362 empirical papers from 2008-2015 and leveraged content analysis to categorise and describe major research themes. They found that xMOOCs dominated the literature, an over-reliance on theory and conceptualisation papers, and that most papers take a neutral stance, with a noted increase in critical discourse. Importantly, they state:

> …though conceptual/descriptive studies have value on their own, many of the studies using this type of the methodology were poorly reported with a lack of empirical data, and did not contribute much to the literature or synthesize current literature; on the contrary, many are superficial reviews. (p. 132)

They also found that only eleven percent of studies examined features of course design and how that related to student outcomes.

Zhu et al. (2018a) explore 146 empirical studies from 2014-2016, focusing on the research paradigms leveraged and most frequent topics in the MOOC literature. The researchers found quantitative methods were most common, followed by mixed methods and qualitative work. In addition to contributing insights on the methods, e.g., that surveys were the most common data collection method, Zhu et al. noted that researchers primarily focused on students. They found that the design of MOOCs was the second-most common topic, but that a focus on the instructors was only apparent in five of the 146 studies covered, which they highlighted (Zhu et al., 2018a).

> There seems to be a growing need to explore [research] related to MOOC instructors, such as instructor motivations when offering MOOCs, instructor design and development experiences related to MOOCs, the instructor role in MOOC design and delivery, and instructors' interaction with TAs, guest experts, and other assistants in MOOCs. (p. 37)

Zawacki-Richter, Bozkurt, Alturki, and Aldraiweesh (2018) augmented the research literature by conducting a content analysis of 362 articles in peer-reviewed journals. The major themes they found were: a) how MOOCs could challenge universities; b) the various platforms on which MOOCs were hosted; c) content and learners; and d) instructional design and quality issues, with most MOOCs suffering from low-quality design. As MOOCs represent a "new" form of open education, though a contested one (Weller, 2014), they discovered considerable attention directed to the notion of openness; particularly, researchers emphasise the need for education to be open, "with regard to people, places, and methods" (p. 251).

Joksimović et al. (2018) conduct a systematic review of the models describing how people learn at scale. They note that, despite the explosion of empirical work considering MOOCs and online learning, the causal links between learning outcomes and learning processes were unexplored. Further, they note that much of the empirical work that has been conducted on MOOCs seeks to understand the associations between student engagement and behaviour patterns and student outcomes, and is often agnostic of contextual variables that might moderate both engagement and outcomes. They propose a framework intended to guide future work that is based on an established model of student engagement that accounts for the association between contextual factors, student engagement, and learning outcomes.

Gardner and Brooks (2018) investigate the literature around predictive models that have been developed to account for student success in MOOCs. They provide a critical synthesis of 87 studies seeking to understand the trends in modelling between predictors and student outcomes, as well as, when applicable, the underlying theoretical model. They note several methodological gaps, including extensive filtering of the data when analysing subpopulations and ineffective evaluation of the learning models. Furthermore, Gardner and Brooks (2018) note why the unique characteristics of MOOCs justify developing predictive models distinct from traditional educational environments. Whereas traditional analogue educational environments are rich in demographic data but sparser in behavioural data, MOOCs suffer from the opposite problem. This means that, while a robust literature has developed around analysing student behaviour in MOOCs, progress in understanding questions about behaviour patterns potentially differentiated along demographic lines can be difficult to tease out.

2.4 Themes of Interest

Several aspects of these literature reviews captured my attention. First, I was struck by the lack of overall attention to underrepresented learners. This was notable given the discourse of MOOCs democratising education when they first emerged. While the theme of openness was noted (Zawacki-Richter et al., 2018), and researchers had paid ample attention to the student demographics and enrolment and completion inequalities (Hansen and Reich, 2015; Ho et al., 2015), understanding what factors were driving these trends was less prominent (Deng et al., 2017). Indeed, while the explosion of data resultant from MOOCs has been lauded, utilising this data in ways that unveil potential insights into student outcomes demographically differentiated remains a weak spot in the literature (Gardner and Brooks 2018; Joksimović et al., 2018).

Second, the empirical literature was deeply impressive. The application of novel data methods to uncover relationships between student engagement and outcomes was consistently emphasised as ground-breaking for education (Gardner and Brooks, 2018; Joksimović et al., 2018). It was noted, however, that better understanding these relationships and how they relate to specific subpopulations of learners was needed (Gardner and Brooks, 2018; Joksimović et al., 2018). Furthermore, while many theories of student engagement and learning were considered and quantified, these models tended to emphasise the micro level dynamics operative in the distance education ecosystem (Zawacki-Richter, 2009), particularly data traces from virtual learning experiences providing insights into student behaviour and outcomes. Less common were attempts to account for the overall socio-technical system design that may be contributing to these outcomes (see **Section 4.4.4** and **Appendix 4.1** for further discussion of the micro, meso, and macro levels of the distance education ecosystem).

While some reviews found that theory and conceptual papers were dominant (Bozkurt et al., 2017; Raffaghelli et al., 2015; Veletsianos and Shepherdson, 2015), this was especially notable early on in MOOC development. Later literature reviews noted the prominence of quantitative work (Zhu et al., 2018a; Veletsianos and Shepherdson, 2016). Some reviews (Joksimović et al., 2018; Gardner and Brooks, 2018) focused explicitly on the quantitative literature.

The call for more qualitative work, however, was made early in the MOOC debate (Veletsianos and Shepherdson, 2016; Liyanagunawardena et al., 2013). Additionally, a need to better understand producers was noted (Zhu et al., 2018a; Deng and Benckendorff, 2017; Veletsianos and Shepherdson, 2016; Gašević et al., 2014), as well as the general low-quality design of most MOOCs (Zawacki-Richter et al., 2018; Velestianos and Sheperdshon, 2016). Calls for more research into the experiences of underperforming and underrepresented learners were also made (Deng et al., 2017; Liyanagunawardena et al., 2013). The emerging critical discourse was also noted (Bozkurt et al., 2017; Ebben and Murphy, 2014).

Several other interesting features emerged in this review. For example, the specific teaching and learning models used in MOOCs received attention from many researchers (Joksimović et al., 2018; Gardner and Brooks, 2018; Deng et al., 2017). Additionally, considerations like the fact that most of the MOOC research was produced in the West were described (Zawacki-Richter et al., 2018). The distinction between cMOOCs and xMOOCs, and how to conceptualise different kinds of MOOCs, was also discussed frequently (Ebben and Murphy, 2014; Liyanagunawardena et al., 2013). That MOOCs were characterised by massive dropout (Jordan, 2014) was noted in virtually all reviews.

Based on the literature above, I further examined two bodies of literature when scoping my research questions. First, I explored relevant empirical literature that shed insight into how underrepresented learners were using MOOCs. Second, I reviewed the emerging critical work referenced by Ebben and Murphy (2014) and Bozkurt et al. (2017) in search of insights into why MOOCs might be underperforming on this dimension.

2.4.1 Underrepresented Learners in MOOCs

As noted in **Section 1.6**, underrepresented learners, for the purposes of this thesis, connotes people without a tertiary degree, or from a low-SES background, or both. A selection of the MOOC literature, reviewed below animates the interest in these two dimensions of being underrepresented. While MOOCs are serving millions of students, learners without a tertiary degree are less likely to enrol and complete MOOCs compared to learners with a tertiary degree. Similarly, learners from low-SES backgrounds are less likely to enrol and complete MOOCs than their peers from high-SES backgrounds. These two findings have been replicated multiple times in the literature, though more work is needed in investigating them.

Christensen et al. (2013) completed one of the first analyses on who was taking MOOCs. They report:

> the student population tends to be young, well-educated, and employed, with a majority from developed countries… 83 percent of students have a post-secondary degree (2 or 4 years), 79.4 percent of students have a Bachelor's degree or higher and 44.2 percent report education beyond a Bachelor's degree. (p. 1)

These findings were reported in *Nature* (Emanuel, 2013), displayed in **Figure 2.2**.

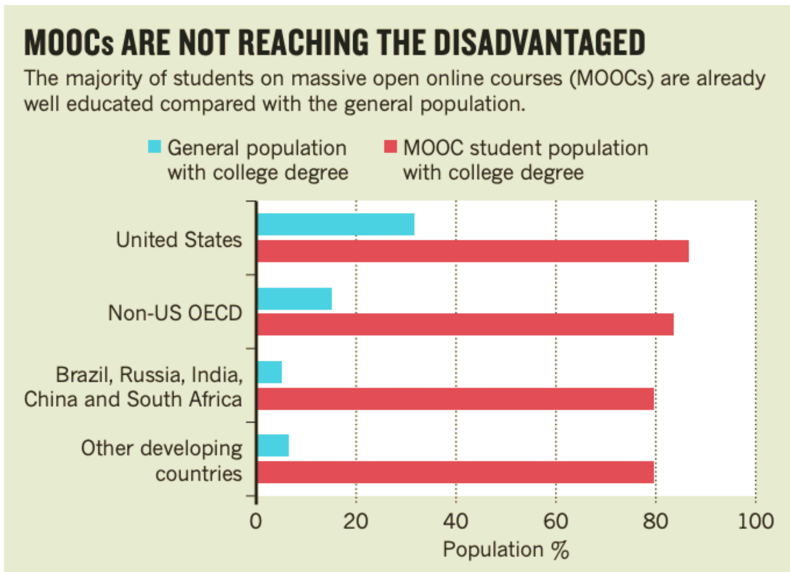


Figure 2.2: MOOCs are not reaching the disadvantaged. From Emanuel, 2013.

A report by MIT and Harvard provides insight on initially observed MOOC trends on edX (Ho et al., 2015). Highlighting the attrition that has become a common observation among MOOCs, the report states that of the over 3 million students who signed up, 1.3 million students never began the course. Furthermore, roughly 65 percent of MOOC students already held a bachelor's degree, and less than 10 percent obtained a certified credential. These findings are illustrated in **Figure 2.3**.

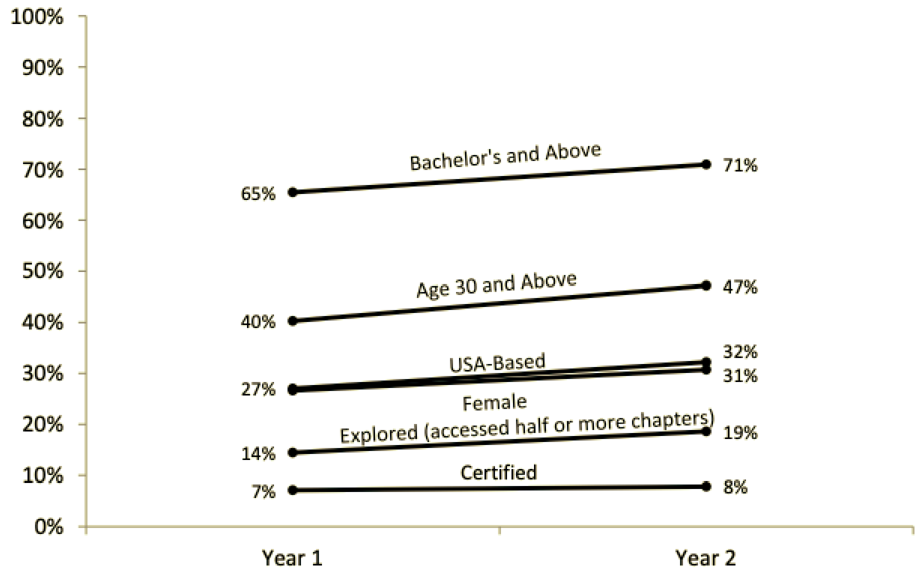


Figure 2.3: MOOCs reach the already-educated. From Ho et al., 2015.

Hansen and Reich (2015) match self-reported mailing addresses to Census data on median household income and educational attainment and compare these to the general population through "a case-control study, with edX enrolees as cases and a synthetic set of 1-1 matched controls by geographic area, assuming that controls are unlikely to be enrolled in edX given the large population size" (Hansen and Reich, 2015, p. 3). **Figure 2.4** shows the average median income and the average number of years of education for more than 160,000 edX MOOC users, compared to the general population. Again, it shows us that MOOC users were disproportionately well-educated and wealthy compared to the average American.

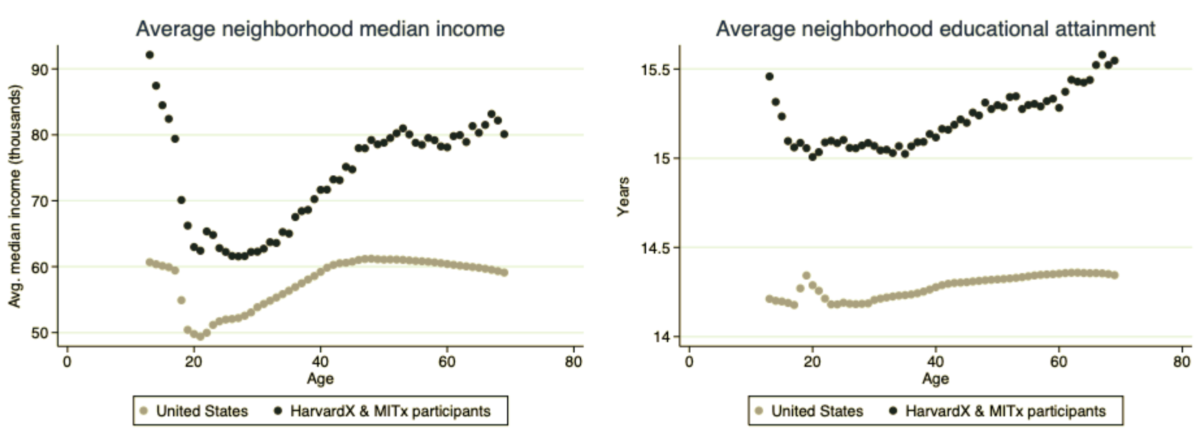


Figure 2.4: Median income approximations and educational attainment for a sample of edX participants, 2012-2013. From Hansen and Reich, 2015.

Van de Oudeweetering and Agirdag (2018) conduct a systematic review of MOOCs and their implications for social mobility. They find that, of the more than 400,000 MOOC users included in the studies they cover, nearly 80 percent already held a college degree. They suggest that while MOOCs may represent lower-cost and more flexible models of higher education particularly suited to traditionally underrepresented learners, these learners still face several barriers that contribute to their relative lack of enrolment and completion, including a lack of technology access, information asymmetries, and pre-existing knowledge barriers (Oudeweetering and Agirdag, 2018).

Not all studies were so bleak. Some studies did report findings that were at least provisionally positive regarding the motivations for underrepresented students enrolling in MOOCs, even if underrepresented enrolment was still disproportionately low. Dillahunt et al. (2014) analysed data from six Coursera courses. Through survey data from more than 40,000 students, the researchers identified a target group who self-identified as “being unable to afford to pursue a formal education” (p. 178) and a comparison group. By comparing demographic variables, along with motivation and course engagement variables, the researchers found that learners in the target group were primarily male, over 25 years old, and held less than a 4-year college degree. They reported that, “although the comparison group had a significantly higher completion rate overall than the target group, the target group had a statistically significant higher rate of completing courses with certificates of distinction” (p. 191). The target group demonstrated stronger levels of motivation on practical considerations, including being geographically isolated from a higher educational institution, and having a strong motivation for taking MOOCs for professional advancement. A similar finding is reported by Zhenghao et al. (2015), noting that traditionally underrepresented learners were more likely to be taking MOOCs for professional advancement.

Stich and Reeves surveyed 2,634 MOOC users from the USA to understand their demographic backgrounds (2017). They report that their study:

> …replicates findings that suggest MOOC participants are already educationally advantaged… In addition, data indicate that while underserved users were more likely to take MOOCs for educational advancement, they were also less likely to complete MOOCs. (p. 58)

There was one paper that suggested MOOCs were working well for underrepresented users, but it defines underrepresented uniquely. Researchers from Duke University defined underrepresented learners as: learners under the age of 18, learners over the age of 65, and learners who otherwise would not have access to the course material (Schmid, Manturuk, Simpkins, Goldwasser, and Whitfield, 2015). The conclusions deviated from the existing literature by concluding that, in fact, underrepresented learners were benefitting significantly from MOOCs. Their data was derived from thirteen MOOCs administered by Duke University on Coursera in the fall of 2014 and comprised a sample of 31,000 learners.

The literature confirmed non-tertiary educated learners, and learners from low-SES backgrounds, were less likely to enrol and complete MOOCs (Hansen and Reich, 2015; Ho et al., 2015; Emanuel, 2013). Not all the insights were disparaging, however, as the findings from Dillahunt et al. (2014), Zhenghao et al. (2015), and Stich and Reeves (2017) indicate that traditionally underrepresented learners, while a lower proportion of the total enrolments, were in fact more likely to be enrolling in MOOCs to expand educational and professional opportunities.

2.4.2 Critical Commentary

Some observers have critiqued MOOCs as an extension of a neoliberal political economy seeking to minimise the role of the state in education and to commodify teaching and learning (Jones, 2015). These critiques are complemented by a critical chorus detailing the downsides of data-intensive platform capitalism (Srnicek, 2017; Zuboff, 2015), algorithmic decision-making (Knox, 2018; Prinsloo, 2017), yielding products that apply the problematic features of humanism onto digital education (Knox, 2016), which simultaneously reproduce existing economic inequalities in the developed world (Meaney, 2018), and impose a new form of digital neocolonialism on the developing one (Adam, 2019; Altbach, 2014). While many of these critiques are specific to MOOCs, others weave between a focus on MOOCs and a critique of digital education and ideologies driving it more generally.

Rhoads, Berden, and Toven-Lindsey (2013) make several critiques of MOOCs based on the power dynamics of elite universities. They suggest the epistemological foundations of MOOCs are rooted in a conception of knowledge transfer and delivery. This ignores how knowledge is produced and the relationship between knowledge and power. This conception of knowledge might contribute to the further privileging of academic fields that benefit more capitalistic models of education, as well as reflect a neocolonial impulse in developed-world knowledge dissemination. Furthermore, Rhoads et al. (2013) question the pedagogy underpinning MOOCs, cautioning that the highly structured, teacher-centric model of knowledge dissemination does not empower learners. Finally, MOOCs produced by elite universities serve to extend and codify the prestige and cultural hegemony of already entrenched institutions of higher education.

Martin Weller, in his 2014 book *The Battle for Open*, highlights several challenging dimensions of MOOCs, particularly the rise of the xMOOC. He recounts the familiar origin story of the cMOOC, centred on a faculty member providing an open, scalable, and social virtual learning experience. The xMOOC turn, characterised by the hallmarks of Silicon Valley, sought to problematise education as fundamentally broken and in need of disruption. Weller, paraphrasing Henry Petroski, suggests, "society forgets fundamental lessons in bridge design every 30 years, because that is the average length of an engineering career. The same may be true with educational technology, except that it is a form of wilful amnesia" (p. 129). Weller discusses how the xMOOC phenomenon neglected the history of experimentation and research from the Distance Education movement of the preceding four decades. Weller is not exclusively critical, noting that the media attention to MOOCs did spark a renewed interest in distance learning generally. Rather, his point is that the xMOOC created more work for itself by seeking to reinvent a very difficult to construct wheel already long in the making.

Perrotta and Williamson (2018) lament the alleged objective use of cluster analysis in learning analytics research, claiming that "cluster analysis operates as a 'performative device' that translates clusters of digital data about learners into socially negotiated 'materialisations'…phenomena that emerge when the social world is rendered traceable and visible" (p. 4). This is primarily due to the subjective nature of how cluster analysis is executed, given that it relies on myriad subjective decisions of educational researchers, including which features to analyse, how to measure the distance between those features, and the appropriate number of clusters to select, among other considerations.

Jeremy Knox of the University of Edinburgh has developed a research program examining MOOCs through what he terms critical posthumanism. He takes issue with the underlying assumption of MOOCs that students are self-directed, autonomous individuals with a universal desire to learn, which he claims are problematically humanistic (Knox, 2016). Knox is critical around the discourse of access and democratisation, suggesting that access alone is insufficient for promoting more equitable education. He calls to open the processes of technology production and for a more critical analysis of the more essentialist and instrumental views in education that consider technology to be an inherently unproblematic good.

In a more recent contribution, Buchanan and McPherson (2019) lament the datafication of education. They express concern that the ideology of Silicon Valley will come to dominate teaching and learning, which could risk fraying the relationship between student and teacher and further alienate students. This datafication could result in students becoming, “more enmeshed in an ever-intensifying network of visibility, surveillance and normalization’, where the ‘embodied expert judgement’ of their teachers is displaced by disembodied algorithmic and adaptive decision-making technology.” (Buchanan and McPherson, 2019, p. 40)

Taskeen Adam (2019) argues that MOOCs propagate a neocolonial, Westernised epistemology that neglects more local forms of knowledge. She asserts that MOOCs exacerbate historical inequalities and that they reflect a techno-capitalist, neoliberal agenda that seeks to commodify education. She concludes with constructive recommendations for how to include more marginalised groups in the MOOC development process, though voices caution that this ought not lead to issues of adverse incorporation, whereby marginalised groups may be exploited.

Adam continues this work through qualitative empirical studies on MOOC producers. In two recent papers, Adam (2020a; 2020b) reports findings from interviews with 27 MOOC designers, many of whom come from traditionally underrepresented backgrounds themselves. In the first paper, she identifies a lack of epistemic diversity among curricular approaches. Adam then develops her conception of an ‘embodiment of openness’ to describe the way in which MOOC designers should approach their work, arguing that MOOC designers should manifest a form of openness, as opposed to merely implementing their learned conceptions of open educational practices (Adam, 2020a).

Adam’s second article is based on the same 27 interviews and investigates how designers conceptualise injustice and whether and how they attempt to account for this in their design (Adam, 2020b). Adam focused on material, cultural-epistemic conceptualisations of injustice in her analysis. Adam finds that different MOOC designers emphasised different dimensions of injustice in their own practices. Novel interventions to support MOOC access in the context of material injustice were also noted. For example, designers formatted content into zip files, created transcripts to serve those without meaningful access to video, and facilitated some of the learning through WhatsApp, a less data-intensive platform (Adam, 2020b).

A prominent source of the more critical critiques of MOOCs is the journal *Learning, Media, and Technology*. In a recent paper which charts hopes for the next decade of educational technology research (Selwyn et al., 2019), the editorial board notes several important features of the educational technology debate requiring further investigation. One prominent example is that policymakers typically problematise the individual in these debates, focusing on how to improve digital skills and technologies, unfairly placing the agency on the shoulders of the individuals, and ignoring the broader contexts. The authors claim that these perspectives are anchored in a neoliberal belief in technology development and dissemination, often predicated on a techno-optimist assumption that technology is inherently good. The authors call for more theorising about how digital technology can facilitate more equitable learning for all (Selwyn et al., 2019).

2.4.3 Literature Review Synthesis

The empirical MOOC literature focused on demographic enrolment and completion rates presents clear insights. First, underrepresented learners are less likely to enrol in and complete MOOCs (Hansen and Reich, 2015; Emanuel, 2013). Some traditionally underrepresented learners, however, do enrol in MOOCs, and are more likely to be doing so for professional advancement (Dillahunt et al., 2014; Zhenghao et al., 2015). As suggested by Van de Oudeweetering and Agirdag (2018), however, these learners face significant barriers to success. Additionally, many of the more advanced learning analytic methods leveraging big data that had received so much attention were not utilised to understand the engagement patterns of underrepresented groups (Gardner and Brooks, 2018).

The critical literature also inspires a great deal of consideration. It broadens the MOOCs debate to include various branches of sociology, postmodern theory, and philosophy. It also proposes some theories for why MOOCs have struggled to democratise learning. At the same time, as noted by Bozkurt et al. (2017), many of these papers do not leverage empirical data to buttress their claims. Furthermore, Bozkurt et al. (2017) noted that questions of access and equity were not featured as prominently in the critical analysis compared to other issues.

In summary, MOOCs clearly struggled to meet their original aims to democratise education. Much of the empirical literature described this reality, but mostly neglected to comment on or seek to operationalise what was driving it. Those that did comment on it primarily attributed MOOC failings to long-noted digital divides in terms of both access and utilisation (Van de Oudeweetering and Agirdag, 2018; Hansen and Reich, 2015). On the other hand, the critical literature noted a number of possible explanations for why MOOCs failed, e.g., that MOOCs were embedded in a neoliberal (Adam, 2019; Jones, 2015), techno-optimist ideology that neglected traditional teaching and learning insights (Weller, 2014), did not adequately centre the learner, and presumed, either through omission or commission, a widely attained autodidacticism in society (Knox, 2018; 2016). These were often well reasoned but not further explored or tested, and as a result left idling as conjecture.

These competing discourses differed in other important ways. The empirical camp reflected a positivist or post-positivist orientation toward social science. This approach maintains a belief that approximately accurate, though imperfect, descriptions of reality are possible through the careful collection of data. Data can then describe reality in an exploratory nature, typically generating new hypotheses, or can test and verify existing hypotheses. The critical camp, on the other hand, engaged in something different. Existing data was sometimes used to illustrate points, but the causal attribution, while implied, was left unstated and unexplained. When original data was collected, it was typically qualitative, and the claims that were made with this data sought to attach them as evidence of broader sociological theories or to help generate new ones, without specification for how they might be verified or falsified. What made matters somewhat more obscure is that the explicit articulation of ontological orientation and epistemology, and even methodology in the case of the critical camp, was often not specified.

I did not necessarily know how to reconcile these camps. Indeed, I still do not. Broader debates occurring simultaneously in the academy in the form of a less charged rerun of the paradigm wars (Schuessler, 2018), and in broader popular culture in the form of fake news and misinformation

(Kofman, 2018), however, exposed me to even more dimensions of these ontological and epistemological quandaries. All these forces ultimately forced me to consider what I might claim as my fundamental orientation toward the nature of reality, as well as what I believe to be the most responsible, reliable, and valid way social scientific research can be conducted to draw accurate conclusions reflective of that reality. I engage with these questions in the next section.

2.5 Methods to Consider

The literature review identified fruitful areas to investigate in order to better understand my central interest in how institutions of higher education might provide inclusive learning opportunities at scale and what pedagogical strategies and technology design paradigms help toward these aims. The literature review also inspired serious concerns of how to investigate these questions in the context of academic research. The transdisciplinary nature of MOOC research and the burgeoning yet robust academic literature surrounding them follows in a common tradition of educational research: it is fragmented, disciplinarily cloistered, and typically internally consistent and valid given a certain set of ontological and epistemological assumptions, yet not generalisable. On the one hand, this suggests that selecting a particular dimension of the MOOC literature to focus on, say, learning analytics, may be a more highly levered way to contribute to the advancement of MOOC understanding. Narrowing my focus too much though risked excluding some of my original animating questions, which seemed an error to me, both because it would be somewhat inauthentic and because it may have precluded me from producing insights that may actually matter. Suffice to say, the investigative roadmap for answering the kinds of questions I was interested in was not straightforward.

These complexities led me down two separate, parallel methodological paths. And while the following distinction is perhaps reductive, it captures the distilled, least common denominated way that I read most of the MOOC literature: one critical, and one more in line with traditional social science. The critical discourse path focused on exploring and theorising the ways in which technology and education reproduced inequality in society. These literatures were typically predicated on relativist ontologies (though this is often unstated), theoretical and qualitative epistemologies (sometimes empirical and sometimes not), and animated by a political and sometimes emancipatory orientation toward their research subjects. The more traditional social science path focused on attempting to apply the scientific method in as objective a way as possible to answer questions about establishing relationships between technology-mediated behaviour and educational outcomes. This literature was typically predicated on realist ontologies (though this is often unstated), positivist or post-positivist epistemologies (mostly quantitative, sometimes qualitative, always empirical), and animated by an orientation earnest in trying to advance knowledge and truth yet sceptical and cautious of the possibility of doing so.

The traditional social science path promised, perhaps above all else, methodological hegemony and respect (Guba and Lincoln, 1994), in addition to the attention of policymakers and the media, and the allure and prestige that comes with leveraging 'big data' to do 'computational social science' (Athey, 2017). More importantly, it is underpinned by a belief in reality, and a belief that reality can be systematically studied, however imperfectly, to incrementally advance our understanding of truth (Hammersley, 2019). The critical discourse path promised vigour and clarity in articulating the ills of inequality and the ways that institutional and artefact design amplified these ills. While morally pleasing, the relativist ontology of these discourses renders much of them rhetoric, further complicated by the irony that many of the claims the genre advances are predicated on the work of more realist, positivist scholarship, a paradigm sometimes simultaneously derided as ideology (e.g., see Culler, 1992).

Given these competing paths, it seemed prudent to take a mixed methods or multimethod approach. This would allow me to utilise the state-of-the-art learning analytic and data mining methods, with a particular focus on underrepresented learners. I could then pair this with interviews of the MOOCs' producers themselves, a recognised gap in the literature, to better understand if and how they were conceptualising inclusion in their practice. In pursuing these research tracks, I would be mindful of the insights from the more critical literature but try to force my critical thinking into operationalisable models, rather than abstract theory. This would provide me flexibility with my methods and an openness to the serendipitous nature of the research process.

Arriving at this set of definitions for my research methods was taxing. Furthermore, there is no function in which to input certain considerations and constraints, academic interests and research domains, and have a clearly defined research design outputted (Gorard, 2010). It required a deep dive into defining my own ontological perspective, considering various methods that aligned with this ontological perspective, and determining a research design paradigm that justified this approach.

The following discourse is how I arrived there. This amounts to a narrative of how I came to my own assumptions regarding the social scientific process, rather than an exhaustive account of the various debates mentioned. Importantly, it concludes with a synthesis of my approach, which then leads into the rest of the theoretical and empirical work.

2.5.1 Positivism and Its Discontents

What is the nature of studying social phenomena? This question encompasses an entire subdiscipline in the philosophy of science; thus, it is beyond my scope to comment on it thoroughly. It is important to briefly situate this debate historically, however, to expose the source of the divide over which methods are best suited to study social phenomena in general and education in particular.

Auguste Comte developed his positive philosophy to be a successor philosophy to theology and metaphysics as a way of explaining the world (Pickering, 1993). He described it as "this special manner of philosophizing that consists of envisaging the theories in any order of ideas as having for their object the coordination of observed facts" (Pickering, 1993, p. 562). Positive philosophy, which he termed 'social physics' and later sociology (Bourdeau, 2021), sought to apply the scientific method to all phenomena. This was predicated on a belief not attributable to Comte specifically, but systematically articulated by him through his Positive Philosophy, which held that the natural sciences provide a model for all inquiry requiring reliance on what can be observed (Hammersley, 1995b). This belief was later augmented, clarified, and supported with mathematical rigour by the logical positivists (Hammersley, 2019).

The early to mid-twentieth century saw what was widely considered a positivist consensus of the philosophy of science among social scientists. In this paradigm, the social sciences heavily emphasised quantification so as to mirror traditional sciences. Evolutions, critiques, and iterations of this worldview roiled the social scientific community in the latter part of the twentieth century in what was known as the paradigm wars (Guba and Lincoln, 1994). As the traditional, quantified, positivistic view of social science was called into question by philosophers of science, furious debates about the categorisation, theorisation, and implementation of these methods began to abound. Instrumental to the decline of positivism as the consensus approach to social science was Thomas Kuhn's *The Structure of Scientific Revolutions*. Kuhn challenged many of the assumptions of the positivist paradigm, including that science is a gradual accumulation of knowledge, that it is agnostic to certain metaphysical assumptions (and in fact, that it has many embedded within it). Kuhn suggested that when a scientific paradigm is saturated (its explanatory power exhausted), it is replaced by new ones (Morgan, 2007). Morgan (2007) describes the shift from the positivist paradigm to the metaphysical one as one not rejecting the insights of positivism but augmenting it, in keeping with Kuhn's requirement that a new paradigm incorporates what works of the old. Therefore, positivism became one of many in a range of methods (Morgan, 2007), which included the constructivist method and the more critical methods predicated on relativist ontologies (Hammersley, 1995b).

It is important to pause here and consider this relativistic turn, as it has profoundly shaped the way in which educational research is produced. Movements from within the philosophy of science, notably, the social study of science, as well as from outside of it, including anthropology, challenged many of the presuppositions of rationality and objectivity foundational to applying scientific inquiry to social matters (Hammersley, 1995b). Phenomenology called into question the objectivity of the fundamental premise of observation as corresponding to reality by claiming that understandings of the world were built upon constructed assumptions. Hermeneutics similarly challenged the basic assumptions of observations. A method emerging from the humanities involving how to interpret texts, hermeneutics eventually came to focus on exposing the challenges of understanding the past. In the twentieth century, Hans Gadamer argued that understanding is based on the interaction between some phenomenon and the a priori assumptions of the observer, which are influenced by cultural and historical circumstances. This led to the assertion that there is no method by which universally valid knowledge can be produced (Hammersley, 1995b).

Post-structuralism similarly denies the possibility of any kind of universally valid knowledge, and even further suggests that knowledge is a product of the pursuit of power (Hammersley, 1995b). Foucault is prominent among these thinkers, as he makes the distinction between knowledge and power inseparable; so much so that he argues all knowledge claims are bound up in a dominant, ideological regime of truth. This dissolved the previously assumed distinction between science and politics.

Foucault's critique and set of methods derived from the humanities share the same foundation as, or in some cases provide the foundation for, a series of 'critical' strands of social science research, extending from broad umbrella terms like postmodernism to specific methodological stances like feminism and critical race theory, which should not be conflated with critical theory itself, which retains scientific elements (Hammersley, 1995b).

Central to Kuhn's critique in *The Structure of Scientific Revolutions* is the incommensurability thesis, which holds that competing paradigms are incompatible. Pragmatism, as articulated by Rorty (1999), the rise of mixed methods (Johnson and Onwuegbuzie, 2004), and other critiques of the metaphysical paradigm (Gorard, 2010; Morgan, 2007), suggest that ontological inflexibility is unnecessary; these critiques generally reject the strict Platonism embedded in the paradigm debates. While these alternative approaches are appealing, they mostly sidestep the thornier philosophical paradoxes about the nature of reality and truth (a pragmatic move, to be sure), and certainly do not resolve them (Feilzer, 2010). Therefore, in determining an approach to social science research, a fundamental choice seems to emerge: follow a theory of knowledge production that adheres to the basic structure of scientific inquiry, or to follow a different approach that prioritises rich description, understanding, and theorising, though potentially predicated on a relativist viewpoint.

2.5.2 Post-positivism and Subtle Realism

The paradigm wars engendered a new humility among positivists. Positivism is now often used derisively, though many of its fundamental tenets still govern social science research, particularly of the quantitative empirical type. Post-positivism emerged from positivism, hedging on its original claims to fundamental truth and objectivity, though remaining committed to the existence of a reality that is not subject to multiple valid forms of understanding. In his essay on the *Postpositivistic Science*, Phillips (1990) articulates several central tenets that define post-positivism today.

Post-positivism accepts the notion of multiple realities to a certain extent; different people in different societies may have competing views about what is real. Post-positivism, however, retains a commitment that one of these views, or, even more specifically, the possibility that a composite version of these views, represents a most correct, accurate understanding of reality. This contrasts with the relativist, who is committed to the idea that all such views are equally valid claims to reality

(Phillips, 1990). The post-positivist view accepts the social construction of reality along similar lines, conceding that different people in different societies believe different things, informed by their own histories and customs and practices. All the post-positivist is interested in ensuring is that such beliefs are open to being researched and evaluated with evidence against some criteria to determine the veracity of those beliefs. Finally, and perhaps most importantly, post-positivism is undergirded by a belief that objectivity is a regulating ideal in the pursuit of truth; this is required to guard against sloppy inquiry, though it may articulate an ideal never fully realised (Phillips, 1990).

Different versions of realism have emerged from the post-positivist camp, adhering to a belief that the best way of going about understanding reality is through systematic observation, but the realists are unified in assigning somewhat less certainty to the capacity of an individual to be able to do so objectively. Critical realism, as articulated by Bhaskar, is one such philosophy (Bhaskar, Collier, Lawson, and Norrie, 1998). Critical realism does, however, retain a commitment to social action in a way that may be problematic. Subtle realism is an even more nuanced approach to social scientific research characterised by a commitment to the scientific method as the best option for learning about and understanding reality, though it asserts that this notion of reality is separate from the observer, and it dispels of the political component. Subtle Realism, coined by Hammersley (1992), is distinct from both critical realism in its non-political commitment, and naïve realism. Naïve realism, closely related to the traditional positivistic view, ties knowledge to direct contact through the senses. Subtle realism, in contrast, asserts:

> There is a single reality (not multiple realities corresponding to different perspectives); that the researcher is part of this reality not separate from or above it; that it is possible to gain knowledge of the phenomena that make up this reality, but that beliefs cannot be *logically* derived from, or be proven absolutely via, sense impressions or any other kind of immediately given data; that a distinction must be drawn between what is true and what can be believed with justification, the latter being decided on each occasion according to what is currently beyond reasonable doubt; and that any understanding or knowledge produced comprises answers to particular questions about the phenomena, rather than capturing those phenomena 'in themselves' – in other words, it cannot simply reproduce them. (Hammersley, 2021, p. 2)

Importantly, this approach can be taken for both quantitative and qualitative methods (Maxwell and Mittapalli, 2010).

2.5.3 Opposition to Relativism

Mark Noll, a historian of Christianity, begins his book, *The Scandal of the Evangelical Mind,* with the following succinct yet devastating statement: “this book is an epistle from a wounded lover” (Noll, 1992, p. ix). This closely approximates my relationship with the critical discourses of the educational research literature. Noll’s book laments the foundational anti-intellectualism of evangelical Christianity, with its neglect of “sober analysis of nature, human society, and the arts" (p. 4). In my quest to understand the shortcomings of MOOCs, the critical discourses’ clarity and urgency intrigued and shaped my thinking. In examining the ontological and epistemological foundations of these discourses, however, I realised that pursuing this research would perhaps mean suspending my belief in reality and our, albeit limited, capacity to systematically study it.

First, there was the constant theorising. Attaching manifold labels to the rise of MOOCs like neoliberal (Adam, 2019), techno-optimist (Mirrlees and Alvi, 2014), neocolonial (Altbach, 2014), and capitalist (Knox, 2016; Hall, 2015), I scoured for articles that set up these claims as hypotheses to be verified, falsified, or explored by data, and struggled to do so. Furthermore, I engaged other literature documenting the use and abuse of terms like neoliberalism (Rodgers, 2018), which had become a catch-all phrase for scholars to criticise nearly all market-oriented, technical, capitalist innovations, deployed with “pejorative intent yet at the same time apparently increasingly promiscuous in application” (Peck, 2013, p. 133).

This scepticism toward theory without subsequent scientific scrutiny, or even really the possibility of systematic evaluation, is supported with lucid detail by Stephen Gorard (2004). He writes:

> The use of theory, in education research for example, often involves the 'adulation of great thinkers' such as Lyotard, Vygotsky or Foucault according to Tooley and Darby (1998, p.56). As they describe it, this is not a scientific approach to explanation through the use of theory, and does not involve testing or specifying criteria for failure of the theory. Rather, it appears to stem from a literary criticism background, which rewards ingenuity in applying literary ideas from one writer to the writing of another. It is common for 'researchers' in this tradition to try

> and explain some new phenomenon using the thinker's framework, but they do so by only arguing for it...(Gorard, 2004, p. 3)

He continues:

> Knowledge for them is, anyway, only meaning. 'Realities are discursive; that is, there is no direct access to a reality 'outside' discourse' (MacLure 2003, p.180). Research is here merely the deconstruction of meaning rather than a search for the truth (or preference) or practicality (what works). (p. 10)

Additionally, there is a tendency for ambivalent merging between theorising and description (Hammersley, 1995b). This type of work is often couched in the language of being critical. However, as Hammersley notes:

> While, in Hegel and Marx sceptical arguments were kept in bounds by a historically emerging philosophical framework, one that was held to be eventually capable of objectively comprehending the true and the good (see Forster 1989), no such principled restriction of scepticism is available within postmodernism. Here, it can only be restrained in an ad hoc fashion, producing what Woolgar and Pawluch (1985) refer to as ontological gerrymandering. (Hammersley, 2005, p. 179)

Which builds off ideas from his 1995 book, the *Politics of Social Research*:

> The focus of critical attention becomes precisely such attempts at epistemological grounding, which are seen as the source of modern political oppression….At the same time, the permanent revolution of critique, which is proposed by poststructuralists and postmodernists seems to leave little scope either for knowledge of the world or for political commitments beyond simple negation or affirmation. Epistemological critique has swallowed up its political counterpart, preserving appearances only through impersonation. (p. 33-35)

Much of the critical discourse in educational research, including MOOCs, tends to buckle under its own weight. The scepticism of any framework leading to a knowledge claim, including the belief that science is merely a means of social legitimation for expressions of dominance and power, undercuts its own claims to insight. Rather than deal with this, adherents of critical discourse revert to merely insisting on deconstruction as an end in itself, what Ball (1995), paraphrasing Eco (1986), refers to as 'semiotic guerrilla warfare.'

This is not to dismiss the notion of theorising altogether. On the contrary, detailed synthesis of evidence postulating a new conceptual framework is a valuable method in social science research, and an essential aspect of theory-building research. I pursue such an approach in one of my subsequent chapters. In what tries to be a more modest exercise, however, the knowledge contribution is proposed as a conceptual framework that can be further iterated and tested, rather than a theory, which asserts far more universal applicability and requires concurring evidence as such (Hammersley, 1992).

2.6 Conclusion: Determining Methods and Research Design

My thesis project was informed by the wide-ranging literature and debates described above. My research interests centred on contributing to certain gaps in the literature, including: a) leveraging quantitative methods to better understand how underrepresented learners in MOOCs were performing; b) conducting qualitative interviews of these MOOC users to better understand their experiences; and c) conducting qualitative interviews of MOOC producers to understand how they were conceptualising inclusion for underrepresented learners in designing and building MOOCs. To do so, I determined I would take a subtle realist ontological approach, providing for both adherence to traditional social science methods and consideration of the often-clarifying potential insights from the critical literature while leveraging a mixture of methods. Originally, I intended to write two qualitative chapters, including a review of the student perspective, which is much-needed in the literature as well, particularly from underrepresented learners. However, amidst running my pilot study, I began to develop an intuition about the reasons MOOCs struggled to democratise learning. As noted in the literature review of this chapter, there was ample description and acknowledgement of the failure of MOOCs. Simultaneously, there was vivid criticism, derived from methodologically unclear, and potentially epistemically inadequate, investigation programs.

In maintaining an interest in the insightful framing of MOOCs from the critical camp but seeking to maintain fidelity to my ontological and epistemological orientations, I sought to develop a potentially operationalisable explanation for why MOOCs had struggled to democratise learning. This would be based on the existing literature and empirical data, and it would seek to build a more stable, or at least epistemically adequate, bridge to the critical insights. I termed this explanation ‘hegemonic design bias,' submitted a paper with an overview of it to the Oxford Symposium on Comparative and International Education, and was awarded a best paper prize, one of five from a pool of 600 papers submitted. A faculty member at Cambridge and an editor of the British Journal of Educational Technology also provided a favourable review, substantive feedback, and recommended I submit it to the journal. With these signals, I began to develop these ideas further. This led to a workshop submission and acceptance to the International Conference on Learning and Knowledge (LAK), where my ideas were well-received and improved upon at the Fairness and Equity in Learning Analytics Systems (FairLAK) workshop.

At this point, while I had already conducted my student interviews, the student interviews became supplemental to my thesis project. Instead, my focus would turn to the production of MOOCs specifically, so as to include my paper on hegemonic design bias. This decision was further buttressed by the noting of a recent reduction in theory work in educational technology in general (Reeves and Oh, 2017), and the status of distance education as a relatively young, under-theorised field more specifically (Zawacki-Richter, 2009). Additionally, I was encouraged by the mention in Bozkurt et al. (2017) of the need for greater development and utilisation of frameworks for inclusion in the MOOCs field, and its call for conceptual frameworks and empirical research to form a greater complementarity. To make this point, Bozkurt et al. (2017) quote Morrison and Werf's illustrative claim that "there is a symbiosis between theory and practice, and, for educational research, they cannot flourish without each other, even though they may have difficulty in living both with and without each other" (Morrison and Werf, 2012, p. 399).

Thus, the three primary contributions of my thesis developed. They influenced each other, insofar as the reading and thinking required to do my quantitative and qualitative chapters provided insights into the MOOC research and design process for my theory-building research. This influence, however, was somewhat serendipitous, not necessarily intended, and not carried out in a methodologically exact way. For these reasons, deeming my thesis process a series of independent papers and leveraging a mixed or multimethod research design seemed fitting, and authentically reflected the "higgledy-piggledy" nature of the research process (Kettley, 2010, p. 117).

I thus explored various methodological frameworks that would allow me to pursue such an eclectic project. Mixed methods emerged with the potential to fill this gap. As the mixed methods literature has evolved, so too have the number of frameworks categorising mixed methods. Many of them have strict requirements, such as formal integration of research questions and methods or conclusions during analysis (Yin, 2006; Teddlie and Taskashori, 2006). Furthermore, many of these frameworks require specification of the questions and methods beforehand, which does little to allow for the interplay between various methods, in which they build off and potentially inform each other. While some authors take a more relaxed approach to defining mixed methods (Onwuegbuzie and Johnson, 2006; Onwuegbuzie and Leech, 2004), a more flexible overall research design seemed more suitable. Gorard (2010) and Reeves and Oh (2017) call for an approach where the specific research methods are not defined until the specific research questions sought to be addressed are clarified. This approach was better suited to being called multimethod, as my three papers evolved concurrently, somewhat serendipitously, and were not formally integrated (Hunter and Brewer, 2015).

While a winding route, I came to understand my research philosophy and design in the following manner. I would produce three independent papers: one theory-building, one quantitative, and one qualitative. I would execute them based on a multimethod research design framework where, while all discrete papers, the development and execution of each one influenced the other. All would be underpinned by a post-positivist, subtle realist orientation to social science research, and would be unified in focus on better understanding why MOOCs have struggled to democratise learning for underrepresented learners.

3 RESEARCH QUESTIONS AND METHODS, CONTEXT, ETHICS, AND LIMITATIONS

3.1 Outline of the Chapter

Section 3.2 revisits the three core papers that comprise this thesis, further specifies the research questions and sub-questions investigated in each, and briefly describes the methods of doing so. **Section 3.3** details the contexts in which this research took place and the timeline of execution. **Section 3.4** considers the ethical challenges of conducting this research and what mitigation strategies were implemented. **Section 3.5** discusses the key limitations of these research approaches, which are expounded upon further in subsequent chapters.

3.2 Research Questions, Sub-questions, and Methods

As discussed in **Chapter 1**, the original aims of this thesis were animated by three research questions:

- **RQ1: What dynamics of the educational technology production ecosystem enable or constrain institutions of higher education in the provision of MOOCs and similar virtual learning experiences for underrepresented learners?**
- **RQ2: How are traditionally underrepresented learners engaging with MOOCs and similar virtual learning experiences?**
- **RQ3: What pedagogical and technology design strategies are useful to employ in attempting to build inclusive MOOCs and similar virtual learning experiences?**

Chapter 2 details how these questions were initially interrogated, which helped to clarify and specify them further as social scientific research questions amenable to investigation through established methods in the educational research literature. Notably, instead of pursuing a narrowly defined mixed methods project subject to more restrictive methodological synchronisation, I was guided by the research questions themselves and crafted a unique, multimethodological approach to my investigation (Hunter and Brewer 2015; Gorard, 2004). This ultimately yielded three discrete academic papers, each complete with its own literature review and methods sections. The specific research questions, sub-questions, and a methods summary of each chapter are presented in the following subsections.

3.2.1 Hegemonic Design Bias: A Conceptual Exploration of Why MOOCs Struggle to Democratise Learning

3.2.1.1 Research Questions

The central animating research question behind this chapter is:

- **RQ1: What dynamics of the educational technology production ecosystem enable or constrain institutions of higher education in the provision of MOOCs and similar virtual learning experiences for underrepresented learners?**

As illuminated in **Chapter 2**, the research literature does not provide an adequate answer to this question. As such, I sought to develop my own conceptual framework to help answer it. Doing so required me to further specify the research question of interest, as captured in the following sub-questions:

- **RQ1: What dynamics of the educational technology production ecosystem enable or constrain institutions of higher education in the provision of MOOCs and similar virtual learning experiences for underrepresented learners?**
    - **RQ1.1 What research methods and theoretical concepts help explore and propose a framework accounting for such dynamics, while adhering generally to a subtle realist research orientation?**
    - **RQ1.2 What would such a framework entail, and what existing MOOC literature lends evidence to it?**
    - **RQ1.3 How might that framework be operationalised and tested?**

Further specifying these questions did lead me to encounter some academic literature that charted a more constructive path in their critiques of MOOCs while still maintaining focus on MOOC potential to reproduce inequality, as well as pursuing such critiques more rigorously (Adam, 2020a; Adam, 2020b; Kizilcec, Davis, and Cohen, 2017; Margaryan et al., 2014). I review many of these research insights in my conceptual development.

3.2.1.2 Method

In a process of theory-building research (Kettley, 2010), hegemonic design bias details a conceptual framework of mechanisms throughout the socio-technical ecosystem producing MOOCs that help account for why they struggle to serve underrepresented students. The framework considers the macro, meso, and micro levels operative in distance education (Zawacki-Richter, 2009) and is informed by socio-technical interaction network theory (White and White 2016; Meyer, 2006), which gives primacy to neither the technical nor the social in analysis. Hegemonic design bias is developed in accordance with a post-positivist (Phillips, 1990), subtle realist (Hammersley, 1992) approach to social science research, seeking to produce socially useful knowledge (Feilzer, 2010). In other words, while some elements are critical, none are relativistic, and all are intended to be practical. Considerations for how to operationalise hegemonic design bias as a series of hypotheses are presented in conclusion. Hegemonic design bias was identified concurrent to the execution of my empirical chapters, so these hypotheses were not tested explicitly.

3.2.2 Adding a Demographic Lens to Cluster Analysis of Participants in Entry-level MOOCs

3.2.2.1 Research Questions

The central research question animating this chapter was:

- **RQ2: How are traditionally underrepresented learners engaging with MOOCs?**

This paper focuses on leveraging a common method of computationally intensive data analysis of previously unexamined data from entry-level MOOCs produced by a major research university in the USA. Certain components of this question are well-represented in the research literature. Particularly, methods for understanding learner behaviour in MOOCs are central to the learning analytics community (Gardener and Brooks, 2018; Kizilcec and Brooks, 2017; Ferguson and Clow, 2015). At the same time, while demographic subgroups are frequently utilised in learning analytic and general educational research literature, few articles used these methods to look specifically at the engagement patterns of underrepresented learners. To pursue these questions specifically, extensive data enrichment and wrangling were required, including the merging of six different data sets, from privacy-sensitive log data to publicly available Census Bureau data. Ultimately, three sub-questions guided the analysis.

- **RQ2: How are traditionally underrepresented learners engaging with MOOCs?**

- **RQ2.1: Do learners in entry-level tertiary MOOCs demonstrate similar patterns of clustering found in the broader MOOC literature?**
- **RQ2.2: Are demographic subgroups of learners, specifically along the educational background dimension, represented equally across clusters?**
- **RQ2.3: What demographic and engagement insights can be unveiled through leveraging a more novel, demographically-sensitive cluster analysis method?**

3.2.2.2 Methods

To investigate how behavioural subgroups are differentiated by demographic characteristics, particularly characteristics revealing dimensions of underrepresented status, I cluster analyse a subset of data from more than 260,000 enrolees in nine entry-level courses based on engagement and achievement data. The clusters are enriched by demographic data, with a particular focus on education level, as well as by approximated socioeconomic status derived from median household income data at the Census tract level from the 2016 American Community Survey.

Two sets of cluster analyses are performed, one common and one more novel. First, I utilise the Manhattan Distance metric and CLARA algorithm to derive clusters. Manhattan Distances measure the relative differences between students based on participation and achievement data. The CLARA algorithm, a medoids-based partitioning algorithm, then groups students into similar clusters.

Next, I utilise the Gower Distance metric, which measures the relative distance between different students based on performance, achievement, and a single demographic dimension, education level. The PAM algorithm, a medoids-based partitioning algorithm (on which CLARA is based) and is optimised for Gower Distance (for which CLARA is not), then groups students into similar clusters.

3.2.3 Building Inclusive, Entry-level MOOCs: Perspectives from Producers

3.2.3.1 Research Questions

The central research question animating this chapter is:

- **RQ3: What pedagogical and technology design strategies are useful to employ in attempting to build inclusive MOOCs and similar virtual learning experiences?**

Existing literature helped refine this question. First, it suggests that the design of virtual learning experiences ought to be based on intentionally specified goals (King et al., 2014). Second, virtual learning experiences are constructed by several different actors, a process that may be difficult to harmonise (Hollands and Tirthali, 2014b). Third, there is ample empirical literature making recommendations for how to design MOOCs. Given that the research-practice gap is a well-defined reality in the production of virtual learning experiences (Buckingham Shum et al., 2019; Bakharia et al., 2016; Price, Kirkwood, Richardson, Case, and Huisman, 2016), it is worthwhile to consider whether the existing literature, or any theoretical or empirical constructs at all, guide production.

To that end, my research question was specified to include the following sub-questions:

- **RQ3: What pedagogical and technology design strategies are useful to employ in attempting to build inclusive MOOCs and similar virtual learning experiences?**
    - **RQ3.1: How are MOOC producers conceptualising inclusion for the students that will use the courses they are building?**
    - **RQ3.2: What processes and practices are they engaging in toward producing inclusive MOOCs?**

3.2.3.2 Methods

I conducted six semi-structured interviews of MOOC producers, including Professors guiding the development and implementation of the course, the Instructional Designers bridging pedagogical and technology design, and Program Managers focused on overall program goals and execution. In my interviews, I focus on the personal backgrounds of the subjects, as well as the environmental context in which they are building MOOCs. Alongside this, I ask specific questions regarding the technical production process. This balance aims to reflect the challenge of designing MOOCs as neither explicitly technical nor social.

Thematic analyses of interview data are utilised to determine themes describing the processes and practices taken by the producers. I try to stay close to the data in my analysis, seeking to illuminate the reality described according to the producers themselves, and how this may relate to constructs in the existing literature or emergent constructs from the producers. The analysis does not, however, seek to infer or extrapolate ideological meaning or significance beyond what is explicitly discussed.

3.3 Context and Timeline

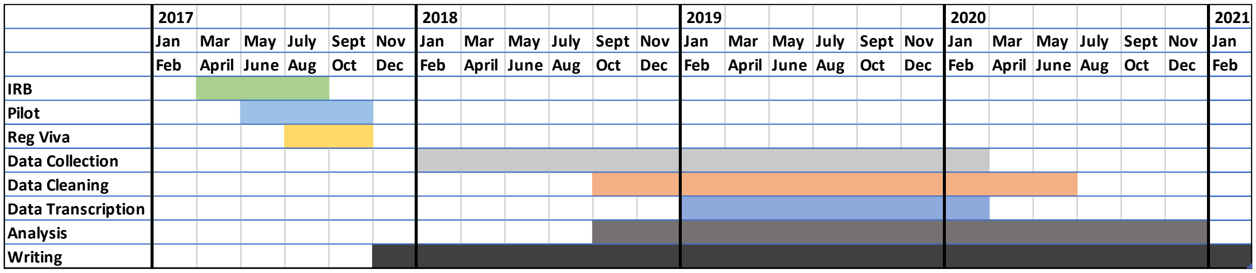
3.3.1 Context

I conducted my PhD research between 2016 and 2020 as a student and then as a candidate at the University of Cambridge Faculty of Education. I was a member of Churchill College, known as the premier science and technology college at the University of Cambridge. Very fortunately, I was funded by the Gates Cambridge Trust, established by the Bill and Melinda Gates Foundation. I was also fortunate to maintain a formal academic visiting appointment with a major research university in the USA, which provided me access to MOOC data and the opportunity to interview MOOC producers. To adhere to a high level of privacy and duty of care for my research participants, I choose to not disclose this specific affiliation. This matter will be further considered in the ethics section.

3.3.2 Timeline

During the fall of 2016 and the spring of 2017, I pursued research methods coursework at the Faculty of Education at Cambridge. In the summer of 2017, I conducted a pilot version of my study to familiarise myself with big data educational methods and to refine my qualitative interview plans. I then produced an initial version of the first three chapters of this thesis which outlined the scope of my project and included a fourth chapter of pilot findings. I defended this work and passed with minor corrections during my Registration Viva, becoming a formal PhD candidate in the fall of 2017. In the spring and summer of 2018, I was in the USA conducting fieldwork, further familiarising myself with big data educational research methods at my host institution, implementing a survey that contributed to my quantitative study, and starting the process of cleaning and merging samples of the various datasets that would ultimately yield my final data sample. Additionally, I conducted my qualitative interviews. For the remainder of 2018 and 2019, I continued to clean my data and began the process of analysing it, in addition to transcribing and beginning to analyse my qualitative data. This continued well into 2020, during which time I began to write up my results and ultimately produce this thesis. This timeline is depicted in **Table 3.1.** During my doctoral studies, I also pursued other opportunities at the intersection of educational policy and technology, including working as a consultant for the Markle Foundation, completing a research internship at Facebook, and completing a visiting research fellowship at the Brookings Institution.

Table 3.1: Timeline of Doctoral Work



3.4 Ethics

Several ethical considerations were required to pursue this research project. The primary source of guidance for these considerations was the Ethical Guidelines for Educational Research produced by the British Educational Research Association (BERA, 2018).

3.4.1 Institutional Affiliation, Duty of Care, and Anonymity

As noted earlier, in addition to my academic affiliation at Cambridge, I maintained an academic affiliation with a university in the USA. I choose to not disclose the institution to attempt to maintain the strict confidentiality of my research participants, particularly the MOOC producers I interviewed. This follows the guidance in sections 40 and 41 in the Ethical Guidelines for Educational Research from the BERA (2018).

As working professionals, it is important to ensure as close to absolute anonymity as is possible for the content of their interviews. As my project is inherently collaborative with my host institution, and I am using purposive sampling, other members of staff might be able to deduce the identities of the MOOC producers I am interviewing. This is a risk acknowledged by the BERA (2018), and I am taking the utmost precaution to mitigate it by not disclosing institutional affiliation and anonymising names and other identifying details.

3.4.2 Internal Review Board (IRB) Process and Approvals

My thesis proposal was examined by Cambridge during my Registration Viva, my application to conduct fieldwork, and risk assessment. The ethical soundness was considered and approved. A copy of this approval is included in **Appendix 3.1**. Additionally, my proposal received Institutional Review Board

(IRB) approval from my host institution, a copy of which is included in **Appendix 3.2**. Only minor changes to my methods were made since these approvals and were approved by my supervisors.

3.4.3 Informed Consent

MOOC producers who agreed to participate in my study were required to complete a consent form. A copy of this consent form is included in **Appendix 3.3**. Additionally, I sought professional services to aid in the transcription of my data, the providers of which signed a consent form attesting to strict anonymity, confidentiality, and data security.

Regarding my quantitative data, matters of privacy and consent are a bit more difficult. The BERA (2018) notes that these matters can be ethically vexing (p. 23). My data was derived from a MOOC platform, edX, which has standardised legal disclaimers that provide for user data to be analysed for academic and commercial purposes. The extent to which users read this form is unknown, though all are required to indicate acceptance of it prior to starting the courses.

According to the BERA:

> It is normally expected that participants' voluntary informed consent to be involved in a study will be obtained at the start of the study, and that researchers will remain sensitive and open to the possibility that participants may wish, for any reason and at any time, to withdraw their consent. (p. 9)

Furthermore, consulting the British Psychological Society Ethical Guidelines (Hewson and Buchanan, 2013), users should be made aware of sufficient details regarding the nature of any study in which they participate.

The edX disclosure, while transparent in explaining the type of research likely to be conducted with user data, obviously cannot include exact details of all the potential studies for which the data will be used, including my own. Furthermore, users should be able to withdraw from participating in a study, should they choose. While this is possible, the process is cumbersome. That said, the edX disclaimer does meet the British Psychological Society's standard for positively affirmed consent (Hewson and Buchanan, 2013), as users must 'check' the box, agreeing that they understand their data may be used for research purposes.

Internet-mediated research is tricky. On the one hand, the ubiquity of internet-enabled platforms and devices, and their continuous aggregation of personalised data, corrodes privacy and anonymity. On the other hand, all these platforms and devices are used freely (for the most part) and with little apparent coercion. The edX platform is a project by Harvard and MIT; their legal disclaimers are industry-standard, and research is regularly produced using data from the platform. While I remain somewhat sceptical of the degree to which users are actually consenting to their data being mined (as opposed to nominally consenting), I place my faith in the larger research and scientific community that, as of now, these practices are ethical.

3.4.4 Data Security

In accordance with my IRB approval, all data was stored on approved storage media, including Google Drive, Dropbox, and secure servers. These can only be accessed with formal credentials from the host institution. The data was not shared with anyone else who did not obtain separate authorisation. The data was de-identified. All information that could be used to identify individual users was removed and replaced with an anonymous id.

3.5 Limitations

There are several limitations of this research project that are important to note. Specific limitations will be discussed further in each chapter.

While multimethodological work is lauded for its utility in synthesising research domains, there is always a risk of fragmentation and dilution. This project is no different.

First, in articulating hegemonic design bias, I raise a number of important philosophical, theoretical, and empirical considerations, then subsequently move on to empirical work that is related but not directly tied to my conceptual development. This reflects an intentional choice made in seeking to remain faithful to the natural development of my research scope and aims. I had the opportunity to include a separate qualitative or quantitative chapter instead of including hegemonic design bias. Such chapters could have, perhaps, more neatly integrated with my other empirical chapters. Particularly, qualitative interviews of underrepresented students, which reveal fruitful insights into their experiences with MOOCs, were left out. Furthermore, explicitly testing hegemonic design bias would have also made sense. As hegemonic design bias emerged concurrent to the execution of my other two chapters, and simply needing to prioritise and define a specific scope of work for my PhD project, I did not pursue this. I would not have likely had time to do so with proper rigour and care. That said, initial feedback received from the scholarly community buttressed my decision to include the paper in my PhD, in the hope of contributing a fresh, if imperfect, take on an important topic in the MOOCs literature.

Regarding my quantitative work, my contribution is noteworthy in terms of methods used and conclusions found. That said, the complexity of those methods and the deviation of those methods from standard procedure is not particularly noteworthy. Cluster analysis of MOOCs data is frequently used in the literature, and the clusters I found reflect longstanding patterns observed by other researchers (Li and Baker, 2018). Furthermore, the learning analytics I based my analysis on could have been more sophisticated, with the inclusion of more types of engagement features on which to base the clusters (Gardner and Brooks, 2018). Several data transformations that could have potentially made my results more generalisable, like weighting the data so that it better reflected a particular population, was not pursued. This is in part due to a desire to report data reflective of actual enrolments and completions, though these will reflect existing biases in the MOOC ecosystem. Some data cleaning procedures, like removing certain subsets of outliers, as well as students for whom certain files were missing across the databases, also reflect the potential introduction of bias. Nonetheless, considering the make-up of these clusters along demographic lines points to important yet qualified insights regarding who MOOCs are serving. Furthermore, the utilisation of the Gower Distance metric, which is straightforward to execute but largely missing in the MOOC literature, presents an interesting way to consider demographic variables in cluster analysis.

The qualitative data sample is small, the analysis subjective, and thus inherently not generalisable. That said, I do believe thematic saturation was reached, and research literature points to thematic saturation being potentially attainable with even low numbers of participants (Guest, Bunce, and Johnson, 2006). Saturation in this context refers to a local conceptualisation; based on the codes I derived, no additional data could be further developed into a separate code or category (Glaser, Straus, and Strutzel, 1968). Given the frequent use of saturation and its myriad meanings, it is important to specify that saturation in the context of **Chapter 6** refers to this narrow conceptualisation (Saunders et al., 2018). It does not refer to having reached a point where no more interviews or data are needed to explore the phenomena of interest; there is no claim to statistical saturation or external validity. Indeed, given the small sample size, it is helpful to consider the qualitative chapter exploratory in nature, requiring further interviews, data, and analysis to defend the results more robustly. While some mitigation techniques were employed, including inter-rater reliability checks at the thematic level, there are methods that could have been used to make my conclusions more valid.

The remaining chapters of this thesis investigate the research questions outlined.

4 HEGEMONIC DESIGN BIAS: A CONCEPTUAL EXPLORATION OF WHY MOOCS STRUGGLE TO DEMOCRATISE LEARNING

In spite of these limitations, we offer this review in the spirit of American statistician John Tukey (1962), who declared that 'far better an approximate answer to the right question, which is often vague, than an exact answer to the wrong question, which can always be made more precise' (p. 62).

– Warschauer and Matuchniak (2010, p. 182)

4.1 Chapter Overview

This chapter presents the conceptual framework hegemonic design bias. **Section 4.2** presents a brief introduction and framing to the significance of these issues and summary findings. **Section 4.3** builds on the literature review from **Section 2.3**, first by broadening the MOOC debate to include issues related to skills-biased technology change amidst increasing global demand for higher education, and then by reviewing in greater detail the extant, more critical literature that seeks to explain why MOOCs have struggled to democratise learning. **Section 4.4** details the theory-building research methodology utilised in this chapter, which ultimately yields a conceptual framework. **Section 4.5** presents hegemonic design bias, first by explaining the term literally, and then explicating its meaning across the macro, meso, and micro levels of the Distance Education ecosystem, enriched by existing MOOCs literature and literature from other disciplines which lends support to its definition. **Section 4.6** considers several ways this term can be operationalised in future research. **Section 4.7** discusses the primary conclusions of this chapter, as well as limitations.

4.2 Introduction

This chapter develops the conceptual framework 'hegemonic design bias' to improve our understanding of why MOOCs have struggled to serve as a democratising force in education. The framework comments on the macro, meso, and micro levels operative in the distance education ecosystem (Zawacki-Richter, 2009) and is informed by a socio-technical lens, which gives primacy to neither the technical nor the social in the analysis of technology (Meyer, 2006). Hegemonic design bias is developed in accordance with a post-positivist (Phillips, 1990), subtle realist (Hammersley, 1992) approach to social research, in what is methodologically considered to be theory-building research (Kettley, 2010). While some elements are critical, none are relativistic, and all are intended to be practical and to produce a useful conceptual framework that can be further refined and tested.

This chapter contributes to the existing literature in two ways. First, it adds an important frame to the debate around MOOCs and online learning more generally. Most research in these areas do not situate the phenomenon of distance learning, and MOOCs specifically, in the context of skills-biased technology change in the labour market. This chapter suggests that the rise of MOOCs and the proliferation of existing forms of distance education coincides with an increasingly technologised economy, where returns to education are accelerating, the gains from which are increasingly captured by a concentrated, socioeconomically advantaged elite. Second, this chapter builds upon existing research into why MOOCs have not democratised education in their originally intended manner by identifying and clarifying ecosystem dynamics that drive sub-optimal MOOC design for underserved students.

Hegemonic design bias describes a series of processes, constraints, and biases that optimise MOOC production toward the already well-educated. This is not necessarily done intentionally; rather, it is a function of a series of macro, meso, and micro level factors that combine to produce and compound sub-optimal designs for underrepresented students. Several institutional and cultural factors endemic to higher education, biases embedded in the operational processes of building virtual learning experiences, and the content within and the design of MOOCs themselves, produce and reinforce the skewness of MOOC design toward those already educationally advantaged. At the macro level, the relative importance of knowledge production compared to knowledge dissemination among elite institutions of higher education, the tendency for this focus to produce extremely exclusionary admissions standards, and elitist mimicry resulting in institutional isomorphism all influence the design of MOOCs. At the meso level, a process termed 'early-adopter iteration bias' skews this design further; through this process, well-educated users make up the majority of MOOC participants, producing the data that researchers and practitioners analyse to iterate and improve MOOCs. A separate but related process, termed 'research-praxis bias,' further prevents MOOC development from meeting the needs of underserved learners. At the micro level, a series of pedagogical, curricular, and technological design processes compound these issues further. This theory-building research yields a conceptual framework for how to consider the socio-technical ecosystems producing MOOCs. Considerations for how to operationalise the components of this conceptual framework will be presented in the discussion and conclusion.

As specified in **Section 1.6.1** and **Section 2.2.1,** and further clarified in **Section 4.5.2.3** and **Section 4.6.1** of this chapter, 'hegemonic design bias,' and comments about MOOCs more generally, refer to Coursera- and edX-style xMOOCs produced in the USA predominantly in English, and which stipulate open enrolment without entry qualifications, have no barriers to access content (though the content may be copyrighted and thus not meet the 'open' definition of OER), are online and available to anybody with an internet connection, are free to complete though may charge a fee for certification (Deng et al., 2019).

4.3 Literature Review

The review of the literature in **Sections 2.2** through **2.4** examines a considerable amount of the MOOC research and evidence on whether MOOCs are serving learners from underrepresented backgrounds, particularly students without a university degree or students from low-SES backgrounds. The present literature review seeks to build upon those insights. In the first section, the framing of the MOOC debate is broadened to consider the notion of skills-biased technology change, concurrent with rising global demand for higher education, and the hope that MOOCs might help meet these challenges. Then, some of the critical literature that has offered potential answers to help account for the gap between original MOOC rhetoric and empirically observed reality is reviewed. I conclude by reflecting on why existing answers, while helpful, either do not account for a number of factors in the distance education ecosystem or do not frame explanations as operationalisable hypotheses. These shortcomings will ultimately animate the research questions guiding the development of hegemonic design bias.

4.3.1 Skills-biased Technology Change and the Higher Education Wage Premium

Education is not merely the catalyst of human capital. Paraphrasing Lewis Menand, the pursuit and creation of knowledge, its application and preservation, and dissemination, are the central activities of civilisation (Menand, 2010). The field of education and its role in society raises deep philosophical questions, extending well beyond education's role in the economic realm to questions of democracy, self-actualisation, and existence (White, 2013).

At the same time, education's contribution to an individual's economic progress and material well-being cannot go understated. Following the tradition of studying human capital as originally articulated by Gary Becker (2009; 1962), an important predicate of the MOOC debate is formed partly by the role of the higher educational-wage premium in our increasingly technologised economy (Autor, 2019; McMahon, 2018; Becker, 1994). Ensuring the opportunity to gain new forms of knowledge and skills is imperative to building a flourishing society where people of all backgrounds can leverage their unique capabilities to contribute to economic output and general well-being for themselves, their families, and others. The capacity for governments and institutions of higher education to produce this opportunity for as many people as possible remains an aspiration (Escobari, Seyal, and Meaney, 2019).

The last 50 years has demonstrated continuous gains to educational attainment in the USA and around the world (Roser and Nagdy, 2019), and it is generally agreed that the pace of technological change will only increase the wage premium accrued by higher education (Acemoglu and Restrepo, 2018). Klaus Schwab, the founder of the World Economic Forum, has described this process as the 'fourth industrial revolution' (Schwab, 2017). Technological change is altering the nature of the economy, and in doing so, altering the ways in which humans contribute to economic output. As computer power accelerates and costs continue to fall, and an artificial intelligence revolution begins to take place, the skills required to succeed in the labour market will continue to shift at an ever-increasing pace (Meaney and Smith, 2016).

The trend toward labour-replacing automation is detailed in a 2013 seminal study by Frey and Osborne, which predicts that 47 percent of jobs in the USA were at risk of automation. Job dislocation will force workers on the lower end of the skill spectrum to acquire new skills to find employment. The study stated that "…as technology races ahead, low-skill workers will reallocate to tasks that are non-susceptible to computerisation - i.e., tasks requiring creative and social intelligence. For workers to win the race, however, they will have to acquire creative and social skills" (p. 269).

A report by the McKinsey Global Institute examining the labour markets of 46 countries arrived at a similar conclusion.

> While about half of all work activities globally have the technical potential to be automated by adapting currently demonstrated technologies, the proportion of work actually displaced by

> 2030 will likely be lower, because of technical, economic, and social factors that affect adoption. (Manyika et al., 2017, pg. 4)

A number of studies from academics and policymakers alike point to similar trajectories (Acemoglu and Restrepo, 2020; Blair and Deming, 2020; Muro et al., 2019).

Workers will be required to continuously augment their existing skills to maintain employability in the labour market, especially workers on the lower end of the skills spectrum (Escobari et al., 2019; Autor, 2014; 2010), or risk not finding employment at all (Beaudry, Green, and Sand, 2016). Potent evidence of these trends is already in effect. From 2007 through 2019, the share of job openings that required a bachelor's degree increased by more than 60 percent (Blair and Deming, 2020). The COVID-19 pandemic of 2020 accelerated these trends. In the USA alone, the pandemic left nearly 30 million people unemployed, with future economic prospects uncertain. Upwards of 40 percent of the jobs lost during the pandemic are expected to be permanently displaced (Barrero et al., 2020). The economic disruption was disproportionately experienced by industries that employ large proportions of elementary and service workers without a college degree (Autor and Reynolds, 2020).

Initial data supports the notion that many adults are enrolling in MOOCs to advance professionally (Liu, Zou, Shi, Pan, and Li, 2019; Littlejohn and Margaryan, 2014), especially learners from more disadvantaged backgrounds (Zhenghao et al., 2015; Dillahunt et al., 2014). While no studies have yet determined empirically the specific wage premium MOOCs can contribute, initial feedback on why users engage with MOOCs points in this direction. A Coursera study from 2015 found that 72 percent of learners reported career benefits and 61 percent reported educational gains. At the same time, translating skill-building through MOOCs into employment gains may be more difficult; a paper by Dillahunt, Ng, Fiesta, and Wang (2016) suggests that low-income individuals using MOOCs to support employment goals struggle to do so. Furthermore, hiring managers and employers seem to still prefer on-campus-based credentials to MOOCs (Rosendale, 2016). Though many are using them for training within their own organisation, and they do perceive MOOC completion to signal something positive about a potential employee's motivation and self-efficacy (Radford et al., 2014).

4.3.2 Increasing Global Demand for Higher Education

Concurrently with skills-based technology change, the provision of higher education throughout developed and developing countries tends to reinforce inequalities along socioeconomic and racial lines (for the American perspective on this issue, see Carnevale and Strohl, 2013; for the global perspective, see Altbach et al., 2009). Skills-biased technological change in the labour market threatens to exacerbate existing social inequality and economic stratification.

As the international economy becomes increasingly interdependent, demand for higher education has surged. The forces of globalisation, economic integration, advancing technological development, and the emergence of a globalised knowledge network compel students and families to prioritise higher educational attainment as a necessity for social mobility and economic security (Altbach et al., 2009). Governments are charged with nurturing education systems that enable this human capital development to be realised, both to fulfil the expectations of their constituencies and to maintain geostrategic competitive advantages in the globalised economy (Carnoy, 2016). As a result of these trends, the global enrolment ratio for higher education students, the proportion of the student-age population attending higher education, more than doubled between 1992 and 2012 (Roser and Ortiz-Espina, 2013). These trends are expected to continue, predicating an imminent supply and demand gap for higher education globally. A UNESCO report from 2013 writes:

> Thirty per cent of the global population is under fifteen and generally accepted forecasts suggest that…the current worldwide enrolment in tertiary education will grow from 150 million now to 250 million by 2025. Simple arithmetic on these forecasts indicates that the world will need to create four sizeable (30,000 students) new universities every week for the next fifteen years or adopt alternative approaches. (Marope, Wells, and Hazelkorn, 2013, p. 101)

Recent academic research projects that by 2030, some 377 million students would seek to enrol in higher education, and 591 million by 2040 (Calderon, 2018). According to journalistic accounts, India alone will be home to more than 140 million higher education-aged students by 2030; presently, it can only accommodate about one-third of them with existing physical infrastructure (Kim, 2015). While only projections, these numbers suggest a significant supply and demand imbalance.

Developed nations are also struggling to satisfactorily educate their populations to keep pace with an increasingly complex knowledge-based economy. The USA will likely face a shortfall of 12 million higher education graduates in the next two decades (Carnevale and Rose, 2015). These numbers belie a more insidious truth. The imbalance in supply and demand disproportionately affects traditionally underrepresented students. Asymmetries of information and inadequate access to resources can make the higher education process difficult to manage successfully. Increasing competitiveness drives admission rates downward in an attempt to drive prestige upward, oftentimes leaving societies' most vulnerable students, those who stand to gain the most from higher education, the most at risk of never receiving one. Compounded educational deficits beginning in early childhood and primary school make it even more difficult for students from disadvantaged backgrounds to thrive in secondary school and higher education (Reardon, 2011).

4.3.3 The Potential Promise of MOOCs, and the Reality

Given this context, it is no wonder why MOOCs were met with such fanfare. As detailed in **Section 1.6,** MOOCs meet the following criteria. MOOCs can accommodate an unlimited number of students and require no application nor any similar barrier to entry. They are fully completed online and accessible to anybody with internet access, and are courses in a traditional sense, in that they cover a discrete range of content offered by an accredited institution of higher education. They are free to use, and for a fee can be converted to university credit toward a credential (Deng et al., 2019; Hollands and Tirthali, 2014a).

MOOCs were heralded as a disruptive technological force that could help solve the higher education supply-demand challenges while improving access to education for traditionally underrepresented students around the world (Selingo, 2014). MOOCs provided classes from Harvard, Stanford, and the Massachusetts Institute of Technology (MIT). While the brick-and-mortar versions of these schools remain accessible to only a select few, it was hypothesised that MOOCs could perhaps enable anyone, anywhere, to receive a world-class education, at little or no cost (Agarwal, 2013). Universities worldwide have grown more and more interested in MOOCs (Ferguson, Scanlon, and Harris, 2016), even as MOOCs have experienced a traditional technology hype cycle (Bozkurt et al., 2016).

It is intuitive to see the appeal of MOOCs, given the scope of the supply and demand problem and the inequalities in higher education worldwide, as well as the accelerating pace of skills-biased technology change. As the knowledge economy requires more and more learning to secure economic stability, could MOOCs play a role in helping reduce educational and economic inequality? The answer to this question depends on whether MOOCs can effectively serve traditionally underrepresented users. Unfortunately, this hypothesis has yet to be borne out. Moreover, MOOCs may be insidiously widening educational inequality gaps and economic disparities (Meaney, 2018; Van de Oudeweetering and Agirdag, 2018; Hansen and Reich, 2015).

As discussed in **Section 2.3** and **Section 2.4**, MOOCs have struggled to reach underrepresented learners from the start. In one of the earliest MOOC papers examining the demographic make-up of participants, Christensen et al. (2013) report that at least 83 percent of students taking MOOCs had a two- or four-year college degree, at least 79 percent held a bachelor's degree, and at least 44 percent held a master's degree. A 2015 report by MIT and Harvard found similar results. The report found that among the 1.7 million participants across 68 courses, 65 percent already held a bachelor's degree (Ho et al., 2015). A report by Hansen and Reich (2015) shows the approximated average income and average number of years in education for edX MOOC users, indicating that the MOOC users were disproportionately wealthy and educated compared to the average American (Hansen and Reich, 2015). Other papers have found similar results, especially that more highly educated users are more likely to enrol and persist (Engle, Mankoff, Carbrey 2015; Kizilcec and Halawa, 2015).

A 2018 paper by Van de Oudeweetering and Agirdag reviews a number of peer-reviewed research articles about the demographics served by MOOCs and their implications for social mobility. Their findings show that, of the more than 400,000 MOOC users included in the studies they cover, nearly 80 percent already held a college degree. A similar collection of studies aggregated by Meaney and Fikes (2019) accounted for some 2.1 million students, 74.76 percent of whom held a college degree.

While MOOCs are the largest educational experimentation and refinement tools ever conceived (Diver and Martinez, 2015), these features have yet to be fully utilised to understand engagement patterns among non-mainstream MOOC learners (Deng et al., 2017). The extraordinary computing power that has been deployed thus far on MOOC data, while contributing impressively to Educational Data Mining, Learning Analytics, and Machine Learning more generally (Gardner and Brooks, 2018; Siemens and Baker, 2012), has neglected to consider many of the traditional socio-educational problems, including the reproduction of inequality, with notable yet qualified exceptions (Kizilcec, Davis, and Cohen, 2017; Hansen and Reich, 2015). This void has been filled by others in the field of education, though not necessarily in an empirical manner.

4.3.4 Theories of MOOC Failure

The notion that MOOCs might exacerbate inequality was an early worry of many in the education field, and scholars began identifying this as a problem as early as 2012 (Ebben and Murphy, 2014; Daniel, 2012). Though myriad literature reviews have considered the academic research on MOOCs (Zawacki-Richter et al., 2018; Veletsianos and Shepherdson, 2016; Liyanagunawardena et al., 2013), the research is severely fragmented along disciplinary and thus ontological, epistemological, and methodological lines (Bozkurt et al., 2017; Raffaghelli et al., 2015; Ebben and Murphy, 2014). As a result, despite MOOCs receiving an unusual amount of attention in both academic literature and popular media, the myths, musings, and paradoxes (Daniel, 2012) surrounding them as a phenomenon have only grown more nebulous (Littlejohn and Hood, 2018). Much MOOC research falls into the trap of what Wegerif states as either describing reality, or complaining about it (2018; 2013). This has left the field productive yet segmented and disciplinarily self-referential. As a result, while there is widespread agreement that MOOCs have failed to live up to their originally hoped-for potential to serve underrepresented learners (e.g., Littlejohn and Hood, 2018; Rohs and Ganz, 2015; Liyanagunawardena et al., 2014), there is less attention to, and agreement on, why this is the case (Gardner and Brooks, 2018; Joksimović et al., 2018; Deng et al., 2017).

Section 2.4.2 reviewed several of the more critical strands of research that have emerged in the discussion of MOOCs. These included examinations that sought less to explain the failures of MOOCs but instead to situate them in a more critical context, variously challenging the Silicon Valley narrative (Weller, 2015), accusing MOOC providers of ignoring decades of insights from distance education (Weller, 2014), raising concerns over the dynamics of platform capitalism and digital surveillance (Buchanan and McPherson, 2019), and criticising algorithmic decision making (Prinsloo, 2017). The remainder of the literature review in this chapter will focus more narrowly on explanations as to why MOOCs struggled to democratise learning.

In one of the first theoretical attempts to provide explanation, Rhoads et al. (2013) question the epistemological foundation of MOOCs as being rooted in a conception of knowledge transfer, which presupposes that knowledge is merely a product that can be delivered. This conception of knowledge might contribute to the further privileging of fields that benefit more capitalistic models of education, as well as reflect a neocolonial impulse in Western knowledge dissemination. Furthermore, Rhodes et al. (2013) question the pedagogy underpinning MOOCs, cautioning that the highly structured, teacher-centric model of knowledge dissemination does not empower learners. Finally, MOOCs produced by elite universities serve to extend and codify the prestige and cultural hegemony of already entrenched institutions of higher education.

In another more theory-laden attempt, Knox (2016) takes issue with the underlying assumption of MOOCs that students are self-directed, autonomous individuals with a universal desire to learn, which he claims are problematic humanistic assumptions. Knox is critical around the discourse of access and democratisation, suggesting that access alone is insufficient for promoting more equitable education. He further specifies this critique by claiming that MOOCs, as presently conceived, reproduce humanistic notions of space that reinforce privilege and inequality. "It is the humanist tendency to regard bounded and located space with an exclusive authenticity that restricts how the space of education is perceived, and this has significant implications for the way MOOCs are designed and delivered," he argues (p. 212).

Adam (2019) also develops a framework arguing that MOOCs propagate a neocolonial, Westernised epistemology that is not sensitive to local forms of knowledge. She asserts that MOOCs, and the digital divide more generally, exacerbate historical inequalities that need to be considered (Adam, 2019). She pairs this with qualitative, empirical work examining the epistemic orientations that MOOCs designers embed into their practice. She develops new concepts from this work to help explore the MOOC phenomenon in the Global South, calling for MOOC designers to enact an embodiment of openness in their design processes as a way to mitigate some of the inequalities perpetuated by MOOCs (Adam 2020a; Adam, 2020b).

Many scholars comment on empirical gaps observed in MOOC access by tying these gaps to existing theories from broader technology literature, particularly the knowledge gap and digital divide theory. Ebben and Murphy (2014) highlight the problematic socioeconomic dimensions of MOOCs, particularly regarding access to the information technologies required to successfully complete MOOCs. They relay reporting on a failed MOOC experiment with San Jose State University that struggled, in part, because of insufficient computer and internet access, especially among underrepresented learners. Inequitable access to the technological resources required to succeed in MOOCs may well help explain, in part, why they have struggled to serve underrepresented students.

Another attempt to account for MOOC failings comes from Rohs and Ganz (2015) in an article entitled *MOOCs and the Claim of Education for All: A Delusion by Empirical Data*. In addition to reporting on MOOCs produced by German universities, replicating earlier findings of most MOOC participants having post-secondary training or degrees, Rohs and Ganz extend knowledge gap theory and the digital divide to help explain why MOOCs struggle to democratise learning. According to Rohs and Ganz, these concerns can be boiled down to an access gap, a usage gap, and a reception gap. MOOCs require access to internet and technology hardware, which is unequal across different socioeconomic groups, and particularly between the developed and the developing world, resulting in an access gap. MOOCs primarily in English, as well as populated by higher-level university material requiring high levels of motivation and an existing knowledge base, likely drive a usage gap. Finally, the decontextualised, heavily self-directed pedagogical orientation of MOOCs, especially without the supports that a typical analogue university might provide, may drive a reception gap.

Similar themes have been emphasised by other authors interested in understanding why MOOCs are failing to meet their original mission. Literat (2015) notes how difficult it may be to design courses that can meet the needs of thousands of learners across the globe with different educational backgrounds. She continues to argue that, unlike traditional campus-based programs, MOOC providers typically absolve themselves of the responsibility of quality through their terms of use. Literat also echoes the concerns around the digital divide, highlighting problematic features like when students are required to…

> …navigate multiple digital spaces, engage in complex interactions, and read and write multimedia texts. In addition, the vast majority of MOOCs are in English; foreign students need

> a superior level of English language proficiency in order to understand course materials (especially non-subtitled video lectures) and to participate in forums. (Literat, 2015, p. 1,170)

The variety of different payment mechanisms governing MOOCs, including paying for credit, completion, and validation, also create barriers and may explain a dissonance between the language used to describe MOOCs and the way they actually operate.

In a systematic review of the literature, Van de Oudeweetering and Agirdag (2018) offer another set of potential explanations. While MOOCs do indeed represent lower-cost and more flexible models of higher education particularly suited to traditionally underrepresented learners, these learners still face barriers that contribute to their relative lack of enrolment and completion. First, these learners are less likely to have access to the technology required for MOOCs. Second, traditionally underrepresented learners face pre-existing knowledge barriers that prevent them from success. These knowledge gaps may contribute to feelings of panic or inadequacy that may predicate dropout (Van de Oudeweetering and Agirdag, 2018).

There is also ample literature examining the shortcomings of MOOC design and pedagogy itself. MOOCs are found to be overly reliant on a behaviourist pedagogy (Bates, 2012), an assessment echoed by Margaryan et al. (2015) who found that, while MOOCs were well organised overall, they scored poorly on instructional design principles. Nawrot and Doucet (2014) describe time management as the biggest driver causing student attrition, while other authors note that the self-regulation strategies needed to successfully complete MOOCs may bias who MOOCs serve (Littlejohn et al., 2016; Hood, Littlejohn, and Milligan, 2015). While often not the explicit focus of these papers, many of these design shortcomings are noted to be particularly acute for learners without strong academic backgrounds.

4.3.5 Synthesising the Literature

Writing during the ‘trough of disillusionment’ (Bozkurt et al., 2016) in the MOOC hype cycle, Gerard Fischer (2014), in his article examining future research considerations, writes, “underestimation may be based on the current early development cycle of MOOCs and the assumption that their primitive capabilities will remain static and will evolve insufficiently over time” (p. 150). Seven years later, in 2021, while the field continues to mature, there remain ample questions regarding MOOC capacity to serve underrepresented students; indeed, the disillusionment has not yet abated. The scepticism is so pervasive that prominent scholars of the field recently suggested that the original aim of MOOCs to democratise education may have run its course; MOOCs, they argue, are pivoting away from democratising learning and instead to aiding universities in a decades-old core competency of providing revenue-generating continuing education programs (Reich and Ruipérez-Valiente, 2019). At the same time, the importance of distance education more broadly, and of MOOCs in particular, have only come to the fore more prominently amidst the COVID-19 crisis (Bozkurt et al., 2020).

Existing empirical literature reviewed offered much in the way to describe the reality of MOOC shortcomings in terms of the types of learners they enrol (Hansen and Reich, 2015; Emanuel, 2013), in addition to commonly having low-quality pedagogical and instructional design (Zawacki-Richter et al., 2018; Margaryan et al., 2015; Bates, 2012). Some of the more critical literature reviewed did provide interesting starting points to consider for why this was occurring; specifically, articulations of the elitist tendencies in higher education (Knox, 2016; Rhoads et al., 2013) and the digital divide and knowledge gap theory (Rohs and Ganz, 2015; Literat, 2015; Ebben and Murphy, 2014).

At the same time, there were notable shortcomings. The more empirical literature focused narrowly on questions of demographics, enrolment, and completion, or certain dimensions of pedagogy and instructional design, without consideration of some of the broader elements of the distance educational ecosystem that affect MOOC development. Additionally, while the learning analytics literature has evolved considerably and shed powerful insights into the ways learners engage with MOOCs, understanding subgroups of potential non-mainstream learners was a noted need (Gardner and Brooks, 2018; Deng et al., 2017). The theoretical literature itself was similarly fragmented; its typically isolated, ad-hoc conceptualisation of MOOC failures were not necessarily framed as operationalisable hypotheses, and were developed disjunctive from each other, instead of in a compounding, enriching way. Additionally, there were some notable gaps around the specific production ecosystem generating MOOC courseware and the research and development communities complementing this production.

Based on this reading, I sought to build on the existing literature by developing a careful and defensible explanatory model into a coherent framework that conceptualises the mechanisms behind the production of educational inequality observed in MOOCs, in a manner that can be operationalised, while considering the various social and technical dimensions driving this across the MOOC ecosystem. This led me to specify the following research question and sub-questions:

- **RQ1: What dynamics of the distance education ecosystem enable or constrain institutions of higher education in the provision of MOOCs and similar virtual learning experiences for underrepresented learners?**
    - **RQ1.1 What research methods and theoretical concepts help explore and propose a framework accounting for such dynamics, while adhering generally to a subtle realist research orientation?**
    - **RQ1.2 What would such a framework entail, and what existing MOOC literature lends evidence to it?**
    - **RQ1.3 How might that framework be operationalised and tested?**

4.4 Methodological and Conceptual Background

Hegemonic design bias attempts to amalgamate existing empirical and critical MOOC literature into a framework accounting for relevant macro, meso, and micro level factors of the distance education field (Zawacki-Richter, 2009) that contribute to sub-optimal MOOC design for underrepresented learners, while at the same time presenting new conceptual contributions. Specifically, the factors discussed at the macro and micro levels of the distance education landscape draw heavily on existing theoretical and empirical literature. The factors discussed at the meso level represent conceptual development of my own, particularly the notions of early-adopter iteration bias and research-praxis bias, though these too are based on insights from the existing research literature.

Throughout these levels, both social and technical considerations are made, seeking to strike a balance between technological and social determinism. This amounts to a process of theory-building research that ultimately yields a conceptual framework of operationalisable hypotheses, underpinned by a post-positivist, subtle realist ontology, informed by a socio-technical lens.

In the remainder of this section, I first describe the theory-building process I endeavoured, coupled with a re-statement of my explicit ontological commitments. I then consider the macro, meso, and micro levels of the distance education ecosystem, which provides a theoretical infrastructure for my conceptual development, followed by an explication of the socio-technical lens that guided my thinking. After this, I detail core concepts from a variety of academic fields that helped construct hegemonic design bias.

4.4.1 Method

Developing hegemonic design bias takes seriously the calls to define educational conundrums in greater detail, even at the risk of causing problems rather than simply trying to solve them (Biesta, Filippakou, Wainright, and Aldridge, 2019). At the same time, I present hegemonic design bias as a series of hypotheses that can be operationalised and tested, to avoid the trap of offering something that might be "not even wrong," (Jung and Pauli, 1960, p. xxxiii). This strategy attempts to leverage the importance of speculative, abductive reasoning while doing so in a manner bounded by well-defined theory-building principles. The result is a moderately critical yet practical framework that seeks to preserve the falsifiability or verifiability requirement of empirical social science with the important interrogative lens advocated by more critical strands of social theory, and allows for both social and technical perspectives to be considered.

To engage in theory-building is no slight claim. Indeed, theory in educational research is a loaded term (Gorard, 2010; Kettley, 2010). Furthermore, I take seriously the caution of senior academics advising more junior academics to stay away from theory work (Rindova, 2008). Additionally, education in general and higher education specifically struggles to be contained within consistent theoretical or disciplinary bounds (Tight, 2014). Thus, I draw very specific boundaries around what I claim to be developing in hegemonic design bias.

At the same time, I am inspired by the tendency of educational research to be at the "frontiers of knowledge…in the liminal zones where disciplines collide" (Kincheloe, 2001, p. 689). Distance education research exists in a web of complexity and is relatively early in its development. As recently as 2000, the field was considered "atheoretical and primarily descriptive" (Perraton, 2000, p. 1), and a major orienting theoretical framework was not developed until 2009 (Zawacki-Richter, 2009). Jen Ross of the University of Edinburgh, arguing for more speculative research approaches, notes that digital education:

> works with ideas and methods from fields, including cultural studies, informatics and design, as well as from more traditional educational research disciplines such as psychology and

> sociology, and such a variety of influences and sources of knowledge inevitably will lead to the sorts of fractures and tensions that the question of 'what works' attempts to write out. (p. 217, 2017)

Furthermore, according to Selwyn (2012), the overreliance on research question framing as "'best practice,' 'effectiveness' and 'what works'" (p. 214) stymies the digital education research agenda from investigating questions of social importance at the boundaries of educational change. The MOOC research literature in particular stands to gain from more careful and robust theoretical development, as reviewed in **Section 2.4** and **Section 4.3.4**, because existing work is not always operationalisable, and the synchronicity between theory and empiricism is lacking (Bozkurt et al., 2017; Raffaghelli et al., 2015).

For these reasons, I pursue the theory-building research that develops of hegemonic design bias as a conceptual framework, but I also stop short of claiming it as a theory, as it lacks empirical data indicating its universal applicability (Hammersley, 1992).

4.4.2 Developing a Conceptual Framework as Theory-building

At one extreme, developing theory is reserved for giants in a field. At the other extreme, developing theory is as quotidian and mundane as trying to think clearly under conditions of uncertainty.

Taking the more conservative interpretation, I do not claim to have developed a theory; rather, I engage a theory-building process that falls short of completing the full cycle; that is, claiming to have developed a theory would require more evidence (Hammersley, 1992). At this stage in my career and given the emergence of hegemonic design bias towards the later stages of my PhD, successfully testing my theory, processing the data, and analysing results, was infeasible.

Through the theory-building process, however, I develop a conceptual framework seeking to explain a pressing phenomenon based on a critical synthesis of the existing literature, which concludes as a formal statement of hypotheses that can form a subsequent research project. It presents a cogent and (hopefully) compelling take on issues that have increased in relative importance but have been obscured by more arcane and disciplinarily self-referential interests. This approach roughly corresponds to the first three phases of theory-building as defined by Nigel Kettley (2010) in his book, *Theory Building in Education Research*, in which he develops a twelve-phase theory-building process called Synthetic and Transformative Theory Building, inspired by the Cambridge School of Sociology.

Kettley's approach is suitable for several reasons. First, he grounds his development of this approach with concerned reflection on the current state of theory-building in educational research, which he claims is in crisis. For myriad reasons, from education being disputed as a field to residual plaque from the paradigm wars of the 1990s to mere sloppy thinking and writing, educational theory-building is poorly defined. This leaves much of educational research either sidestepping the theory-building question altogether or engaging with theory in an ad-hoc manner (Kettley, 2010).

Second, he grounds his description of theory and theory-building in formal definitions, borrowing from Gioia and Pitre (1990). Theory, Kettley claims, "denotes any coherent description and explanation of observed phenomena which provides a testable, verifiable or falsifiable, representation of social relationships;" building theory, then, is "defined as the process of knowing, perceiving and conceiving relationships, derived from systematic inquiry, which can transcend paradigms if a comprehensive and consistent 'worldview' is developed" (Kettley, 2010, p. 9-10). These are succinct, powerful, and clear definitions.

Following the Cambridge School of Sociology, Kettley's theory-building conforms to a realist, multi-method approach, which ultimately insists on being empirical but is open and flexible regarding how this empiricism is carried out. I was also attracted to this theory-building approach for its belief that research should engage with social problems in creative ways (Kettley, 2010).

Kettley specifies twelves steps in the process, depicted in **Figure 4.1**. In developing hegemonic design bias, I followed the first three. Phase one calls for "Deep reading and transformative deconstruction of existing empirical findings and theoretical representations," followed by abductive reasoning, which leads to phase two, "Framing the 'foreshadowed' problem including its synthetic reconceptualization along cross-paradigm lines and exploring the transformative potential of research" (Kettley, 2010, p. 118). Phase one is reflected in chapter two of my thesis, as well as the literature review of this chapter. Phase two is reflected in **Section 4.5** of this chapter, where I explicitly articulate the conceptual framework of hegemonic design bias. Phase three, which calls for "Development of cross-paradigm research aims, objectives, or questions addressing patterns or deep causes simultaneously" (Kettley, 2010, p. 118), is addressed in the concluding section of this chapter, where hegemonic design biased is operationalised.

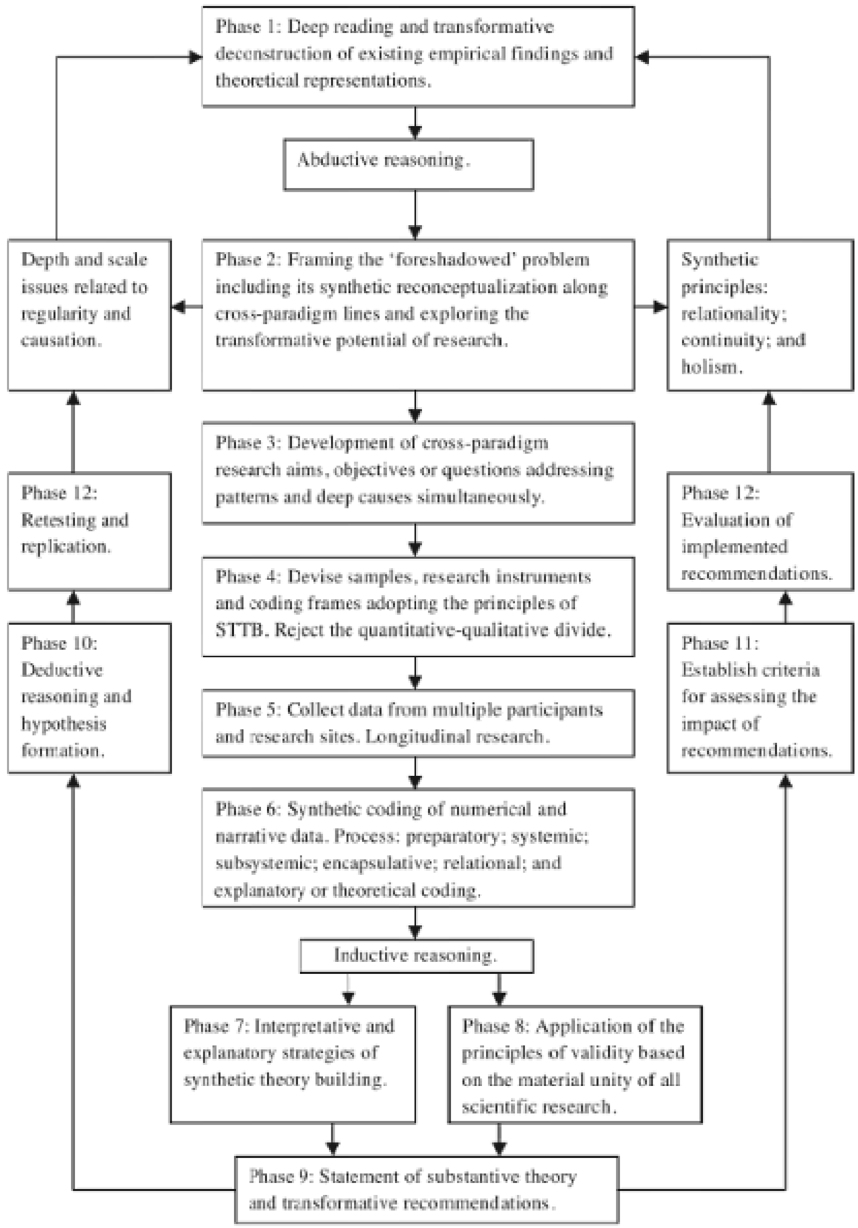


Figure 4.1: The 12 Steps for Synthetic and Transformative Theory Building. Phase one, Deep reading and transformative deconstruction of existing empirical findings and theoretical representations, followed by abductive reasoning, which leads to phase two; Framing the 'foreshadowed' problem including its synthetic reconceptualization along cross-paradigm lines and exploring the transformative potential of research; and phase three, which calls for Development of cross-paradigm research aims, objectives, or questions addressing patterns or deep causes simultaneously, were utilised in developing the conceptual framework, hegemonic design bias. From Kettley, 2010, p 118.

4.4.3 Ontology

Having explicated and attempted to justify my methodological approach, I now turn to the ontology guiding my thinking. This is more thoroughly discussed in **Section 2.5**.

Informed significantly by the work of Martyn Hammersley and others, hegemonic design bias reflects a post-positivist (Phillips, 1990), subtle realist approach to social research (Hammersley, 2019; 1992). In examining the extent to which MOOCs have democratised learning, and seeking to understand why or why not, the goal of developing hegemonic design bias as a conceptual framework is to produce socially useful knowledge (Feilzer, 2010). This is ultimately underpinned by a realist, empirical ontology; that is, social phenomena (in this case, the use of MOOCs and the data generated thereof, as well as how MOOCs are designed and developed) exist independently of researchers' accounts of them. Those accounts can correspond to reality accurately, and those accounts can be investigated, interrogated, and accessed via the scientific method to produce knowledge (Hammersley, 2009). At the same time, this post-positivist, subtle realist approach accepts the limits of positivist essentialism defined in the paradigm wars of the twentieth century and seeks to incorporate the incisive and often insightful orientation produced from more critical perspectives. The incorporation of critical insights, however, stops when these insights move from the bounds of realism into a relativistic perspectivism, an approach often conjoined with outright social criticism with an explicitly political orientation, and often carried out without axiomatic and methodological justification (Hammersley, 1995b).

In short, hegemonic design bias takes seriously the criticism of MOOCs as reproducing social inequalities and not serving in the democratic fashion originally envisioned. Rather than lay this at the feet of an extractive (Buchanan and McPherson, 2019), neoliberal (Jones, 2015) and neocolonial (Adam, 2019; Altbach, 2014) capitalism, hegemonic design bias provides a set of speculative knowledge claims (as a dimension of, as opposed to dichotomous from, reliable knowledge (Hammersley, 2019)) and potentially operationalisable hypotheses for why MOOCs have not served in a democratic way. The goal of doing so is to provide socially useful research for how the MOOC production ecosystem might be improved.

4.4.4 Levels of Analysis for Distance Education

Digital technologies have fundamentally altered the education landscape, allowing new pedagogical developments to emerge and making access to knowledge increasingly flexible and open. While at the start, online education was considered avant-garde, it has become an integral part of how teaching and learning are designed and evaluated. Distance education research, inherently interdisciplinary, has evolved and adapted to meet the demand of studying digital education technologies (Bozkurt et al., 2015). MOOCs represent yet another new horizon in distance education research.

Because of the complexity of educational research and the multidisciplinary frame through which MOOCs can be viewed, it is important to ground the development of hegemonic design bias in an existing framework of educational technology for two reasons. First, it makes the development stronger. A central problem of educational research is that it is fragmented across methodological and theoretical lines. Distance education research, in particular, has been described as severely fragmented, overly descriptive, and atheoretical (Perraton, 2000). "Research questions should be posed within a theoretical framework and embedded in a holistic structure of research areas within a discipline" (Zawacki-Richter, 2009, p. 1), and, until recently, no such framework had been established.

Zawacki-Richter (2009) proposed such a framework based on an extensive literature review and Delphi Study with expert responses from members of the editorial boards of major distance education journals. Through this process, he developed a categorisation of distance education literature and identified both the most important and neglected areas of the field to be considered. He then grouped research themes into 15 different categories and then had the same experts prioritise them. A full description of the Zawacki-Richter classification can be found in **Appendix 4.1**. The fifteen major themes identified are as follows:

Macro level: Distance education systems and theories

Access, equity and ethics (1)

Theories and models (2)

Globalisation of education and cross-cultural aspects (3)

Distance teaching systems and institutions (3)

Research methods in distance education and knowledge transfer (3)

Meso level: Management, organization and technology

Innovation and change (1)

Quality assurance (1)

Costs and benefits (2)

Professional development and faculty support (2)

Learner support services (2)

Educational technology (3)

Management and organization (3)

Micro level: Teaching and learning in distance education

Interaction and communication in learning communities (1)

Instructional design (2)

Learner characteristics (3)

Furthermore, while they are listed in order of importance according to the experts with a score on the right-hand side (1 = most important, 2 = mid-level importance, 3 = least important), all issues areas are significant to the overall development of the field and have an impact on student achievement.

Hegemonic design bias is situated in the macro, meso, and micro framework described. While each issue area within each level is encompassed to some degree by hegemonic design bias, the specification of it as a conceptual framework is more concerned with the delicate ways that each of the issues areas interact in the overall educational technology development ecosystem. That said, a few categories from the above framework do align specifically, particularly: access, equity, and ethics; distance teaching systems and institutions; and research methods in distance education and knowledge transfer, at the macro level; professional development and faculty support; educational technology; and management and organisation at the meso level; and all three categories of the micro level.

Additionally, it is important to note that these categories are not strictly fixed. Indeed, many issues in distance education blend across multiple issue areas. In particular, the way in which research methods in distance education and knowledge transfer interact with professional development and faculty support forms a meso level consideration in hegemonic design bias.

4.4.5 Analytical Lens: Socio-technical Interaction Networks

I anchor my description of hegemonic design bias, in part, in a theoretical framework borrowed from social informatics known as Socio-technical Interaction Networks (STIN) (Meyer, 2006). The STIN framework, developed in the broader discourse of socio-technical systems theory, seeks to privilege neither the social nor the technical while examining socio-technical phenomena. This is particularly important for MOOCs, as they exist as both social and technical artefacts, and seeking to describe MOOCs without accounting for their social or technical dimensions is incomplete. This attempts to avoid both social and technological determinism.

Elements like the exclusionary, institutional isomorphism endemic to elite higher education in the USA (Crow and Dabars, 2015) represent a more social accounting for why MOOCs have struggled to serve underrepresented learners. Elements like early-adopter iteration bias, where data from MOOC early-adopters is analysed and distilled to make prescriptive insights on MOOC design moving forward, is more technical. Both of these elements help form hegemonic design bias, but they represent different disciplinary domains, cause different problems, and require different responses. Neither is exclusively social nor technical, with many interacting and interrelated components that share both social and technical qualities.

Examining MOOCs through the STIN lens is useful. A STIN lens views systems as a network of people and technologies which are inseparable from each other when examining, defining, and analysing the system itself. This avoids the shortcomings of an exclusively Critical Theory of Technology articulated by Feenberg (2008) and the more instrumental view taken by learning analytics. To date, the application of STIN as a lens to understand MOOCs has been small (Jones and McCoy, 2019; White and White, 2016). This may be due, however, to the relative lack of focus on the MOOC production ecosystem overall, or a potential lack of knowledge of the STIN framework itself outside of social informatics, rather than the lack of salience of STIN as a model. Littlejohn and Hood (2018) in their book, *The [Un]Democratising Potential of MOOCs*, do, however, reference STIN as a useful lens to consider MOOCs.

4.4.6 Core Concepts

As distance education spans the fields of computer science, sociology, economics, psychology, and many others, I seek to provide clarity and brief background on the concepts from some of these disciplines that are utilised in hegemonic design bias.

The post-positivist, subtle realist orientation is balanced on one side by an appreciation for the pathbreaking innovations developed by the learning analytics community and the insights these developments provide into technology-enabled learning. At the same time, I am inspired to move beyond describing the ‘what,’ a function done well by learning analytics, and offer suggestions as to ‘why’ we may see the outcomes that we do. Therefore, balancing learning analytics is a perspective from the politics of technology, which suggests all technology has implications for socio-political issues. The diffusion of innovations, borrowed from organisational theory, forms the bridge between learning analytics and the politics of technology insofar as it provides the mechanism through which socioeconomic and sociopolitical considerations shape and influence technical ones.

4.4.6.1 Learning Analytics

Big data analytics are a relatively recent development in educational research. While other fields in the hard sciences and social sciences have used these methods for decades, only during the last decade have they become prominent in educational research. This trend has been predicated, in part, by the proliferation of technologies being used in education for teaching and learning as well as the major growth of online learning educational offerings (Siemens and Baker, 2012). The major methods and tools used in learning analytics and data mining are prediction methods, structure discovery, relationship mining, and discovery with models (Siemens and Baker, 2012). Learning analytics and educational data mining have primarily been used to understand and predict student engagement, dropout, completion, and learning in technology-enabled educational environments. They rely on a wide variety of data sources, from student demographic data captured during course enrolment to student achievement data reflective of learning outcomes to the fine-grained student activity log data in between (Gardner and Brooks, 2018).

4.4.6.2 Politics of Technology

Langdon Winner of Rensselaer Polytechnic Institute asserts that technologies have inherent politics (1980). He suggests that the design of technology "becomes a way of settling an issue" (Winner, 1980, p. 123), meaning that the design dictates implications for usage. This can be intentional, which can be explicitly oppressive and unjust; or, this can be unintentional, which can also be oppressive and unjust, though in a more insidious manner. This notion of politics requires us to consider the existing social structures of society, and how the design of technology might reinforce or reduce those social structures. Who is benefitting from innovation? Who is losing out? Who is being ignored?

In explicating the politics of technologies, Winner (1980) examines the construction of bridges on the Long Island Parkway, designed by Robert Moses and chronicled in *The Power Broker* (Caro, 1974). The bridges were designed to be low in certain areas. Low bridges prevented public transportation, like buses, from accessing certain beaches. The effect was to prevent those who relied on public transportation, low-income minorities in particular, from accessing the beaches (Winner, 1980). In this case, the design of the bridges was carried out to meet specific social ends, exemplifying the ways in which technologies can reinforce existing social structures in society.

The politics inherent to design can be observed in nearly any instance of design: from how seatbelts (Bose, Segui-Gomez, and Crandal, 2011) and buildings (Winner, 1980) are designed to the design of the overall electoral system (Hajnal, Lajevardi, and Nielson, 2017). This is especially true for digital technologies. Consider how most examples of AI are female assistants, while the one who won Jeopardy is male; these designs reproduce gendered stereotypes in society (Mitchel, Ho, Patel, MacDorman, 2011). Predictive policing technologies that are trained on data reflective of grave historical maltreatment of African Americans are another example (Selbst, 2017).

4.4.6.3 Diffusion of Innovations

The diffusion of innovations is a concept developed by Rogers (2010). The theory suggests that innovations diffuse across society along different segments of the population, sequentially through innovators, early-adopters, early-majority, late-majority, and laggards. Rogers notes that early-adopters of new technologies will more likely be well-educated and wealthier. These users have access to more and better information, coupled with a higher tolerance of risk for new products. Early-adopters are also likely to have disposable income and are a more attractive target market toward which to design new products. Innovations are iterated and optimised based on data available from early-adopters.

4.5 Hegemonic Design Bias

Hegemonic design bias describes a series of processes, constraints, and biases that optimise MOOC production in a manner biased toward the already well-educated. This is not necessarily done intentionally; rather, it is a function of a series of macro, meso, and micro level factors that combine to produce and compound sub-optimal designs for underrepresented students.

4.5.1 Hegemonic Design Bias: Definition

At the most basic level, hegemonic design bias is comprised of three terms: hegemony, design, and bias. The central idea is that the design and iteration of MOOCs reflect the preferences and reproduces the advantages of an already elite group; namely, those with a college degree.

4.5.1.1 Hegemony

Hegemony as a concept is most notably associated with Antonio Gramsci, the early twentieth-century Italian socialist who co-founded the Italian Communist Party and served as a member of the Italian Parliament. After Mussolini came to power, Gramsci was imprisoned, despite his immunity as a member of Parliament, during which time he wrote prolifically on political philosophy in journals that were published in 1948, a decade after his death. Gramsci's voluminous and original thought transformed him into one of the most prominent socialist intellectuals of the twentieth century (Buttigieg, 2002). Education and class relations were central to this thought. Gramsci believed that social structures reinforced and maintained the dominant position of a single, ruling, elite class. The state and its ancillary institutions, including educational institutions, operated to prop up and buttress the role of the state and cement the social dominance of the hegemonic class, the bourgeoisie (Mayo, 2008).

Whereas Gramsci may have seen more conspiratorial aims in the works of educational institutions buttressing the ruling class, my assessment is a bit more reserved. While elite institutions of higher education preach the value of inclusion and make some efforts to live up to this value, a series of institutional constraints and cultural tendencies constrict elite higher education's capacity to function as a democratising agent in society. These constraints and cultural tendencies inculcate biases into the institutional design that make it hard to produce educational environments that are inclusive to a broad swath of people. The empirical evidence of this is striking. For example, children in the USA whose parents are in the top one percent of income earners have a 77 times greater likelihood of attending an elite college than children whose parents are in the bottom twenty percent of earners (Chetty, Friedman, Saez, Turner, and Yagan, 2017). In some ways, then, it is not surprising that MOOCs, produced predominantly by elite universities, mimic this tendency by predominantly serving an already advantaged educated class.

The hegemony in hegemonic design bias refers to the asymmetric position of economic and educational power that are features of the educationally advantaged. There are several other asymmetric dimensions between users that emerge in MOOC data. For instance, learners from high-SES backgrounds and from more developed countries are more likely to participate in and complete MOOCs (Hansen and Reich, 2015; Ho et al., 2014; Christensen et al., 2013). In addition to these advantages being sources of asymmetry themselves as variables, they are also typically correlated with higher educational attainment (Brown, Richardson, Hargrove, and Thomas, 2016; Palardy, 2008). While a case could likely be made that hegemonic design bias operates in a similar fashion regarding these variables, that is beyond the scope of this chapter. Furthermore, while dimensions of low-SES do inform how 'underrepresented' is discussed in this thesis more broadly, and empirically pursued in **Chapter 5**, the particular scope applied to hegemony for the current chapter is limited to education level, for the sake of clarity and consistency.

This chapter focuses specifically on hegemonic design bias toward the already educated learner, for two reasons. First, the original mission of MOOCs was cloaked in the language of democratising educational access for those who need it most, i.e., the educationally underserved (Reich and Ruipérez-Valiente, 2019; Rohs and Ganz, 2015; Agarwal, 2013). Second, those with a college degree hold disproportionate economic power in the USA and around the globe and are far safer than those without a college degree from the economic shifts wrought by skills-biased technology change. Indeed, skills-biased technology change, as discussed in **Section 4.3.1**, is likely amplifying the economic security of those with a college degree compared to those without. Furthermore, this is a problem growing in severity. The progression of artificially intelligent technologies is poised to drive the premium for higher and higher levels of education even further (Acemoglu and Restrepo, 2018; Beaudry et al., 2016), and has been made even more acute by the COVID-19 pandemic (Autor and Reynolds, 2020).

The tragedy of the early MOOC experience is that, rather than potentially equip learners without a college degree to adapt economically so as to benefit from skills-bias technology change, MOOCs may have reinforced already-educated classes' relative skills, allowing them to capture an even greater proportion of the economic premium. The interviewees in recent news articles about the MOOC surge during COVID highlight this potential. A medical doctor studying public health, a technology manager studying artificial intelligence, and a business analyst studying to become a machine learning engineer, all via MOOC (Lohr, 2020), reflect what might be considered a stylised fact about the MOOC universe: that they serve already well-educated learners (Meaney and Fikes, 2019). This is fine in and of itself, but when considered in the context of skills-biased technology change, with accelerating returns to more complex work requiring more education (Autor, 2019) and downward pressure on wages and employment levels for the lower half of the skills spectrum, the implications for exacerbating inequality become apparent (Escobari et al., 2019).

4.5.1.2 Design

Design, broadly conceived to include both pedagogy and instructional design, as well as the content that makes up MOOCs, mediates how learners interact with MOOCs. Scholars call this learning design, which describes "the act of devising new practices, plans of activity, resources and tools aimed at achieving particular educational aims in a given situation" (Mor and Craft, 2012 p. 86). MOOC design is particularly unstructured and lacks traditional scaffolds, requiring a high degree of digital literacy, learning autonomy, and background content knowledge from the participants (Littlejohn and Hood, 2018; Koutropoulos and Zaharias, 2015). Additionally, the curricular content of MOOCs is typically quite advanced, often presuming a level of background knowledge that precludes learners from non-college-educated backgrounds, despite the all too frequent claim that there are no prerequisites (Evans and McIntire, 2016, p. 318).

4.5.1.3 Bias

Finally, this is a result of bias. The use of this word is perhaps the simplest to explain yet perhaps the most contested in the field of education. Scholars with a critical orientation might posit that the exclusion of certain types of learners reflects the logic of expansionary neoliberal capitalism and an unrestrained, Western digital neocolonialism (Adam, 2019). On the other hand, bias in a traditional social scientific sense refers to systematic error, usually resultant from some problem arising from data collection or analytic methods that prevent a researcher from accurately determining the truth about some phenomenon. Hammersley and Gomm (1997) take on the ambiguous nature of the term bias as deployed across social science and provide an illuminating discussion and typology of how bias is deployed. They developed a six-part framework depicted in **Figure 4.2.**

In hegemonic design bias, bias is hypothesised as negligent bias, either the result of motivated unconscious negligent bias or unmotivated negligent bias (Hammersley and Gomm, 1997). It is possible that it is a result of motivated and conscious bias, what Hammersley and Gomm term wilful bias, but there is not yet evidence of that, and to pursue it as a hypothesis would require the assumption of malignant motives.

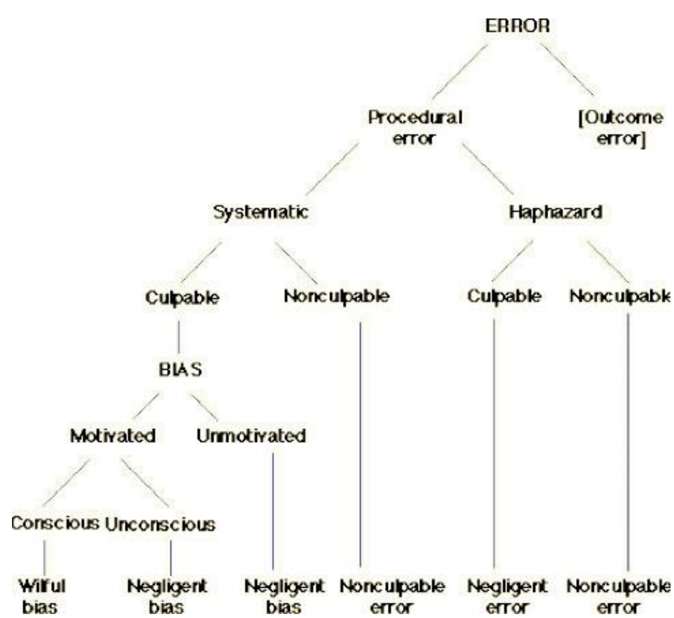


Figure 4.2: A network identifying types of error. From Hammersley and Gomm, 1997.

4.5.2 Hegemonic Design Bias: Explication

Several institutional and cultural tendencies endemic to higher education, biases embedded in the design and production systems of MOOCs, and the content within and the design of the virtual learning experiences themselves produce and reinforce the skewness of MOOC designs toward those already educationally advantaged. These processes are summarised and highlighted in **Figure 4.3**. In the following sections, I analyse the macro, meso, and micro levels in turn.

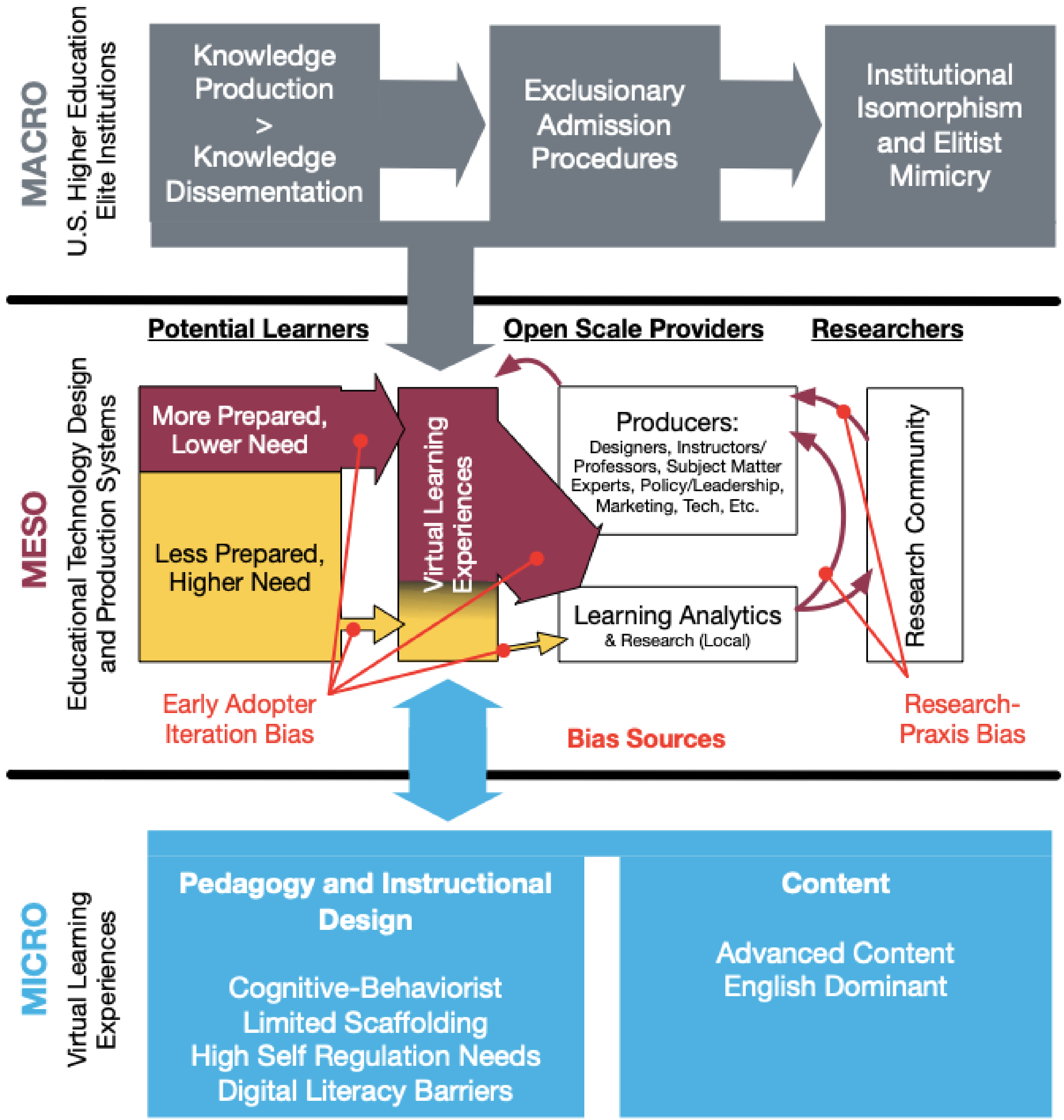


Figure 4.3: Hegemonic Design Bias. At the macro level, the relative importance of knowledge production to knowledge dissemination among elite institutions of higher education, the tendency for this focus to produce exclusionary admissions standards, and elitist mimicry resulting in institutional isomorphism, influence the design of MOOCs. At the meso level, 'early-adopter iteration bias,' whereby already educated users make up most MOOC participants and produce the data used to iterate and improve MOOCs, skews this design further. A separate but related process, termed 'research-praxis bias,' further prevents MOOC development from meeting the needs of underserved learners. At the micro level, a series of pedagogical, curricular, and technological design processes compound these issues further.

4.5.2.1 Macro Level: Elite Higher Education Institutions in the USA: Institutional Design and Culture

Despite their relatively late start in the nineteenth century, when American research universities were formed (Shils, 1978), these institutions have catapulted to the top of global rankings of higher education (Times Higher Education, 2020). They have produced knowledge breakthroughs that have improved the lives of everyone in the world, in addition to educating global leaders who have shaped it for more than a century. Simultaneously, these institutions have become some of the greatest reproducers of socioeconomic inequality today (Chetty et al., 2017), largely through the admissions process, through which these institutions have come to pride themselves on the number of students they exclude. These arguments are not new. Indeed, they are well examined and documented. The only novel contention is that, because of the institutional design and culture of elite higher education, these institutions are less capable of designing systems of any kind, including technological systems, that enable diverse groups of people to learn and flourish.

Crow and Dabars (2015), in their book *Designing the New American University,* help explain that while these elite American higher educational institutions are the envy of the world in terms of research output and scientific breakthroughs, they simply are not designed to provide education to a broad demographic of students. The macro level of hegemonic design bias stipulates three reasons for this, further expounded below. First, professors at these institutions are incentivised to focus on research over teaching. Second, the teaching that does occur is not optimised for high-need students; it has always been to serve the elite, and more recently, to include a small fraction of high-achieving underserved students, excluding the vast majority of even those who are academically qualified. And finally, the tendency for elite institutions in the academy to mimic each other as they position for prestige entrenches these design constraints across most elite universities.

The tension between knowledge production and knowledge dissemination in American higher education, the exclusionary nature of these processes, and the resultant institutional replication are as central to the historical development of the institution as they are essential to its modern design. While American colleges were conceived as knowledge-disseminating institutions for the elite, they have evolved significantly, having built a hyper-competitive and prestige-obsessed knowledge production enterprise on top of teaching colleges (Crow and Dabars, 2015). This new hybrid institutional form has innovated several ways to deal with these competing impulses, such as the widespread reliance on adjunct instructors (Nica, 2018), though it has become increasingly obvious that the knowledge production function trumps the knowledge dissemination one.

When Harvard College was founded in 1636, it was predicated on the Oxford and Cambridge model, with a focus on the teaching of undergraduates in the residential college. This formed the traditional liberal arts college, initially replicated by other Ivy League colleges and still common today at smaller, private tertiary institutions (Crow and Dabars, 2015). The research-intensive American university, with a simultaneous aim of educating young people, emerged in the nineteenth century. This institutional type merged the colonial college, modelled on Oxbridge, with the research-intensive institution, a German model pioneered by the University of Berlin, which focused on knowledge production and graduate training in the scientific method. Johns Hopkins University, which pioneered this institutional type, was founded in 1876 as a private research university (Crow and Dabars, 2015). The former Ivy League colonial colleges grafted research-intensive units complete with graduate training onto their liberal arts schools in the mid-to-late nineteenth century. Around the same time, in 1862, President Abraham Lincoln signed the Morrill Act into law, establishing the American land grant universities, which were explicitly conceived to both pursue applied scientific discovery and innovation as well as educate the citizenry (Crow and Dabars, 2015).

These three strands of higher education in the USA, Private, Ivy League, and Public, emerged as the foundational models of American research-intensive universities with a simultaneous commitment to knowledge production and knowledge dissemination. Roger Geiger, Distinguished Professor of Education at Pennsylvania State University, claims that a set of fifteen of these institutions formed the foundation of the modern American elite higher education system, including the public universities of Illinois, Michigan, Wisconsin, Minnesota, and California; the former colonial colleges of Harvard, Princeton, Yale, Columbia and the University of Pennsylvania; and private institutions including the Massachusetts Institute of Technology (MIT), Johns Hopkins, Stanford, the University of Chicago, and Cornell. These universities coalesced into the proverbial gold standard of American higher education by the early twentieth century (Geiger, 2017).

The institutional organisation of American higher education, especially among elite universities, as well as how elite universities are compared to non-elite universities, is the subject of many volumes of academic literature with nuanced findings and implications. Even the exact definition of ‘elite’ itself is subject to much discussion and contestation. For now, however, there are two useful definitions of elite worth including. The first batch is the gold standard universities described. The next batch of elite institutions are those shaped in large part by the gold standard schools (Crow and Dabars, 2015). This group encompasses some 131 universities which are considered ‘very high research activity,’ or R1, by the Carnegie Classification of Institutions of Higher Education (2017).

4.5.2.1.1 Knowledge Production > Knowledge Dissemination

> IF NORMAL JOBS WORKED LIKE ACADEMIA: ‘Hey, congrats on being hired as a plumber here! You’ll spend most of your normal hours being an accountant, but you’ll be promoted or fired based on how many pipes you can fix on weekends and evenings. (Professor Paul Musgrave, 2019, Twitter)

While knowledge production and knowledge dissemination form dual mandates for the modern American research university, in practice the incentive structures are extremely biased toward knowledge production. This is reflected extensively throughout the culture of research-intensive R1 institutions. Hiring, promotion, and tenure emphasise research over teaching and service. While explicit weights on research, teaching effectiveness, and service are not disclosed, most faculty believe that research and publication strength are required and cannot be compensated for by exemplary service or teaching (Schimanski and Alperin, 2018). ‘Publish or perish’ has become the predominant norm (Cadez, Dimovski, and Groff, 2017; Parker, 2008). Junior faculty are routinely told to focus on research (Boss and Eckert, 2003).

Anecdotal evidence supports the claim that relative focus is placed on knowledge production. In her popular blog, Karen Kelsky (2018), a former tenured academic and department chair at the Universities of Oregon and Illinois at Urbana-Champaign, notes the following advice when applying for academic jobs:

> Top-ranked research universities will, on the whole, have a standard 2-2 load (meaning you would teach two courses each semester of the academic year) in the humanities and most social sciences (and a 1-2 or even a 1-1 or 1-0 in STEM fields). Those universities are obviously

research-centred — so your cover letter should be, too. A cover letter for a position with a 2-3 load and, in most cases, even with a 3-3 load, should still put research first.

> Second- and third-tier research universities — i.e., many second-level state comprehensives, for example — are often what I think of as "aspirational." They are invested in trying to demand more research productivity from new hires despite lacking support for it in terms of teaching-release time or funding. They can make those demands because of the desperate conditions of the academic job market: Departments have their pick of top-tier, highly productive Ph.D.s, and feel empowered to increase their publishing expectations for new hires.
>
> Once you see job ads that list teaching loads of 3-4 or 4-4, you can confidently put teaching first in your cover letter. Two notable exceptions are tenure-track jobs in the City University of New York system and in the California State University system. (Kelsky, 2018)

Many in the academy nominally consider the goals of research and teaching to be complementary (Taylor, 2007). Unfortunately, however, according to a widely cited meta-analysis by Hattie and Marsh (1996), there is practically no relationship between research production and teaching quality. While there are important debates about how teaching quality is measured, the Hattie and Marsh (1996) findings have been replicated across a variety of methodologies (Cadez et al., 2017; Figlio, Shapiro, and Soter, 2015), and anecdotal accounts routinely discuss the higher status attributed to research compared to teaching (Elton, 1996).

Finally, this emphasis on research relative to teaching, especially at R1 institutions, uncritically promotes low-quality teaching, inhibiting these institutions from effectively serving underrepresented students. As Harry Brighouse, Professor of Philosophy at the University of Wisconsin Madison, writes:

> Instructional quality is the most neglected–and perhaps the most serious–equity issue in higher education. Good instruction benefits everyone, but it benefits students who attended lower-quality high schools, whose parents cannot pay for compensatory tutors, who lack the time to use tutors because they have to work, and who are less comfortable seeking help more than it benefits other students. (Brighouse, 2019, p. 25)

4.5.2.1.2 Exclusionary Ethos

The relative importance of knowledge production compared to knowledge dissemination is not the only salient feature of R1 universities to consider. It is also important to analyse the incentives and constraints that guide how faculty at these universities teach when they are required to do so.

As a secondary function of focusing on knowledge production over dissemination, these institutions only offer to educate the brightest students. Faculty at these universities teach carefully curated students who have demonstrated academic competence, ambition, work ethic, and problem-solving skills. These students are the most likely to graduate regardless of where they go to university, yielding the intuitive but nonetheless meaningful reality that the more selective a school is, the higher its graduation rate is (Bowen, Chingos, and McPherson, 2009). These are the easiest students to teach, and faculty can focus on other matters. This has led to a proverbial arms race among high-quality institutions to attain greater and greater selectivity. According to public affairs scholar Chris Newfield (2010), increased selectivity yields more money and higher quality students, lessening the load on faculty who can then focus on research, further enhancing prestige and, eventually, yielding more funding and further increasing selectivity. The race to the top in selectivity is made manifest in elite institutions' obsession with exclusionary metrics, most notably the entrance rate of students who applied to their entering class. In 2014, Stanford University made headlines for admitting a mere five percent of the students that applied (Pérez-Peña, 2014).

The results of these constraints and incentives are considerable. The American higher education landscape has produced a small cadre of rich, elite schools of exceptional calibre, and a large second tier of universities and colleges producing poor outcomes but also serving the highest need students (Crow and Dabars, 2015; Carnevale and Rose, 2015). For example, the Association of American Universities, representing the 60 leading research universities in the USA, enrol just six percent of the total tertiary students in the USA. If you extend this analysis to the top 108 research-grade institutions, a little more than two million students are enrolled, accounting for just 11 percent of total tertiary students (Crow and Dabars, 2015).

These realities are paired with the fact that the socioeconomically advantaged elite are capturing most of the gains from higher education, especially at the most elite schools. Research by Chetty et al. (2017)

finds that roughly one in four students from the wealthiest families in the USA are likely to attend an elite tertiary school, compared to less than one half of one percent for students from families in the bottom income quintile. The result is a set of elite institutions of higher education which optimise for knowledge production ahead of knowledge dissemination, and that are not required to design knowledge dissemination systems that serve diverse learners.

4.5.2.1.3 Institutional Isomorphism

Finally, highly competitive, research-intensive institutions of higher education seek to emulate each other, reifying the institutional and cultural constraints that inhibit their capacity to deliver learning to a broad audience of heterogenous learners.

The tendency for institutions and organisations in a given domain to emulate the patterns and processes of one another is termed institutional isomorphism (DiMaggio and Powell, 1983). Crow and Dabars (2015), citing numerous others, describe how this is endemic to the academy. First, they note that, outside of the church and the law, the academy may be the most tradition-obsessed institution in the world. The ‘filiopietism’, as this is known, runs deep; from the arcane academic regalia and rituals to the bureaucratic processes underpinning the operation, a reverence for tradition pervades higher education. That many in the academy are trained to question and probe the status quo while culturally submitting to its maintenance is paradoxical, though nevertheless real. The filiopietism-derived institutional isomorphism that corrupts the academy is, in part, an obsession with prestige, at least among the most competitive research-intensive universities. As Crow and Dabars note:

> This assertion may seem implausibly reductionistic, or at the very least simplistic, but the unceasing efforts of institutions to replicate Berkeley and Harvard down to the last Ionic entablature or Georgian portico is no mere idle diversion… Ascent in rank brings with it not only enhanced legitimacy but also the promise of greater autonomy and perceived access to more abundant financial resources… (Crow and Dabars, 2015, p. 123).

This incentivises universities to emulate those directly above themselves in the hierarchy.

> Filiopietism inspires the lockstep thinking that produces the set of undifferentiated institutions we might term the Generic Public University and the “Harvard envy” that is endemic to private universities. Despite the plethora of institutional types in American higher education—research universities, liberal arts colleges, regional public and community colleges, and so on—

institutions in each category bear a striking resemblance to one another, and less prestigious institutions seem invariably intent on replicating the organisation and practices of their aspirational peers. Thus, public research universities tend to model themselves on the University of Michigan or the University of California, Berkeley, for example, and their private counterparts strive toward Harvardization…Institutional rankings, such as those proffered by U.S. News & World Report, only exacerbate this compulsion toward replication, as do the practices of foundations and government agencies. (Crow and Dabars, 2015, p. 121)

As Crow and Dabars (2015) recount, citing Louis Menand (2010), this powerful tendency in elite academia can be summarised by Cambridge classicist F. M. Cornford, in his guide for young academics, *Microcosmographia Academica*: 'Nothing should ever be done for the first time.'

4.5.2.1.4 Elite Higher Education as Producers of MOOCs

The institutional cultures and constraints of elite higher education in the USA powerfully shape and reify an organisational model prioritising knowledge production over knowledge dissemination, an exclusionary ethos obsessed with prestige, and a replication process yielding a race to the top of this hierarchy. The institutional and cultural constraints of elite higher education would have little bearing on MOOCs if these institutions were not the predominant purveyors of MOOCs.

Therefore, it is important to establish these are indeed the dominant MOOC course providers. Class Central is a MOOC aggregator that functions as an industry scorecard, among other activities, and is regularly cited in academic studies and reports of MOOCs (see Adam, 2019; Gardner and Brooks 2018; Kizilcec and Brooks, 2017). According to Class Central, in 2019, more than 110 million students took MOOCs offered through over 900 universities and enrolled in more than 13,000 courses, which counted toward 820 different micro-credentials and 50 MOOC-based degrees (Shah, 2019b). Of these, the vast majority are taken and offered by USA-based MOOC providers operating in Silicon Valley and Boston: Cousera, edX, and Udacity. FutureLearn, the U.K.-based MOOC provider affiliated with the Open University, and Swayam, and Indian MOOC provider, both accounted for some 10 million students. Cousera accounted for 45 million; edX for 24 million, and Udacity for 11.5 million (Shah, 2019b). While it is true that USA-based MOOC providers offer courses from a global list of universities, these universities are constrained by the behaviouralist and pedagogically minimalist approach of the

American MOOC platforms (Zhu, Bonk, and Sari, 2018b). In 2019, of the top 100 MOOCs taken, some 36 are offered by premier US institutions, and a full 65 are taken on Coursera, edX, or Udacity (Shah, 2019a). The numbers for 2020, far larger given the COVID-19-induced influx, nevertheless reflect similar patterns of Coursera and edX hegemony, and dominance by elite higher education in the USA (Shah, 2020).

4.5.2.2 Meso Level: Educational Technology Design and Production System

The meso level of hegemonic design bias describes a set of features endemic to the technology design and production systems required to build virtual learning experiences like MOOCs, depicted in **Figure 4.4**. Learning analytics, the process of mining user data to understand engagement patterns and associating this behaviour with learning outcomes, have the potential to provide valuable insights into teaching and learning in these virtual learning experiences (Nguyen, Rienties, and Toetenel, 2017; Lockyer and Dawson, 2011). This may be especially valuable for scaling low-barrier, individualised learning experiences that can reach traditionally underrepresented populations (Aguilar, 2018).

The broader systems in which learning analytics are embedded, however, gives rise to multiple sources of bias that may stymie the efforts to develop these courses into inclusive virtual learning experiences. First, an early-adopter iteration bias may unintentionally lead to design recommendations that serve already well-educated learners (Meaney and Fikes, 2019). Because analytics and research inform practice, if learning analytic data are not adequately disaggregated and heterogenous effects considered, conclusions will be biased toward the majority of users. This will, in turn, drive the innovation and optimisation of the virtual learning experiences to further favour these students, potentially disadvantaging underrepresented learners. Second, 'research-praxis bias,' whereby the producers of virtual learning experiences do not properly benefit from learning analytics and research insights into the virtual learning experiences, might further prevent the design from meeting the needs of underrepresented learners.

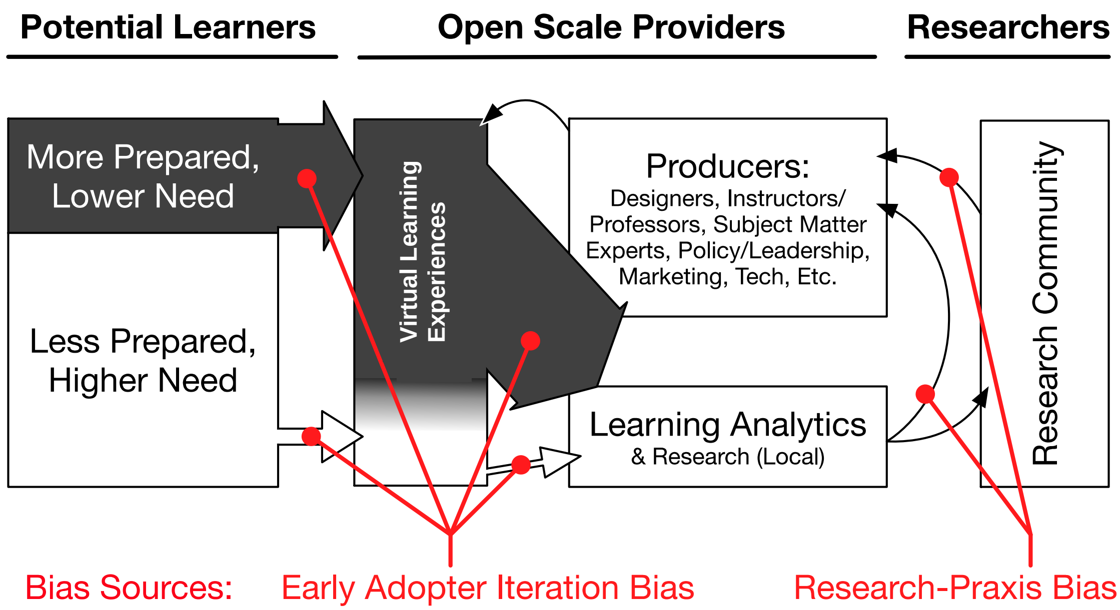


Figure 4.4: The Meso Level of Hegemonic Design Bias: The Educational Technology Design and Production System. The universe of students who could benefit from virtual learning experiences contains a high proportion of less prepared, higher-need students. 'Early-adopter iteration bias' describes the situation in which students from more prepared, lower-need backgrounds disproportionately enter the virtual learning experiences and persist at higher rates. The data corpus produced by the virtual learning experiences reflects the population of more prepared, lower-need learners, and learning analytics and research conducted on this corpus produces results biased toward the majority. 'Research-praxis bias' describes the situation in which producers of the virtual learning experiences receive insights from learning analytics and the research community that is driven by the more prepared, lower need majority, leading to innovation and optimisation of course design that is further away from the needs of less prepared, higher-need students. This is further complicated by the disconnect between the research and practice communities. From Meaney and Fikes, 2019.

4.5.2.2.1 Early-adopter Iteration Bias

Early-adopter iteration bias is a concept developed to account for a series of processes and constraints that optimise the design of MOOCs and similar virtual learning experiences for more prepared, lower-need learners (Meaney and Fikes, 2019). The intuition is grounded in Rogers' (2010) theory on the diffusion of innovations. Early-adopters of technology will often have characteristics different from those of the technology's later users. Learning analytics of massive data sets have focused on behaviour patterns of the average student, who are early-adopters and more likely to be already well-educated (Van de Oudeweetering and Agirdag, 2018; Rohs and Ganz, 2015; Perna et al., 2014). This leads to optimisation and design recommendations driven by insights derived from users less likely to need help. If future course iterations continue to be optimised based on present usage patterns of early-adopters, and if these usage patterns continue to reflect the needs and behaviours of more prepared, lower need learners, this could further exacerbate enrolment and persistence gaps between well-educated and underrepresented learners. Early-adopter iteration bias is illustrated in **Figure 4.5**.

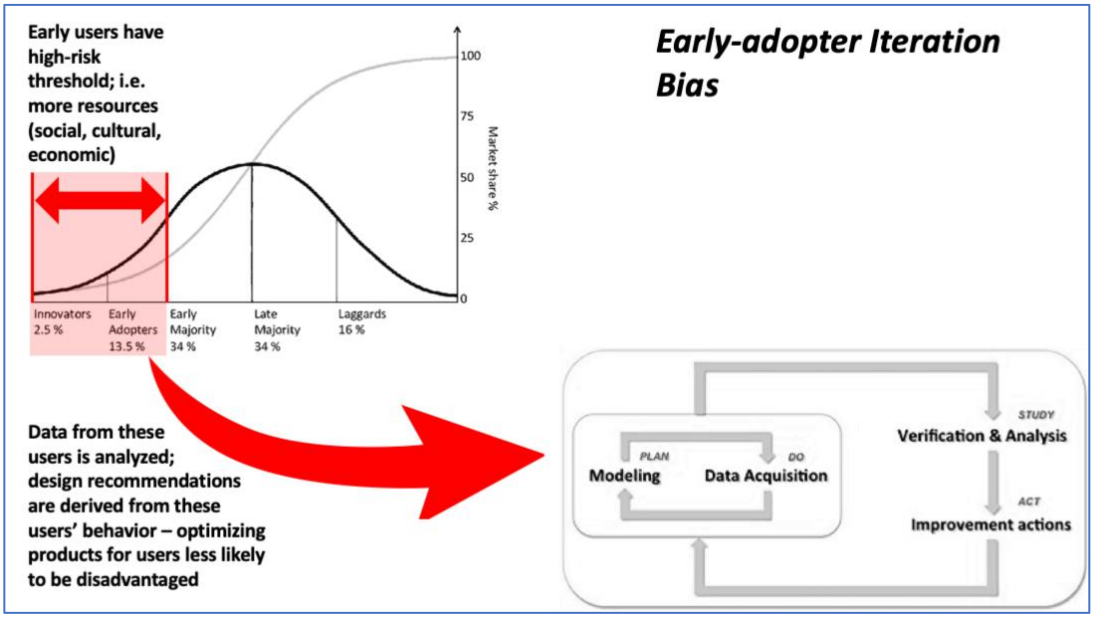


Figure 4.5: Early-adopter Iteration Bias. The diffusion of innovations theory suggests that innovations diffuse across society along different segments of the population, sequentially: innovators, early-adopters, early majority, late majority, and laggards (Rogers, 2010). Early-adopters of new technologies will more likely be well-educated and wealthier. Innovations are iterated and optimised based on data available from early-adopters. From Meaney and Fikes, 2019.

Given the disproportionate rate of already well-educated learners using MOOCs, it is possible that early-adopter iteration bias has already entered the MOOC production system. **Figure 4.6** highlights the educational attainment of users studied in eight learning analytics papers over the past few years. Nearly 80 percent of users already held a college degree**.**

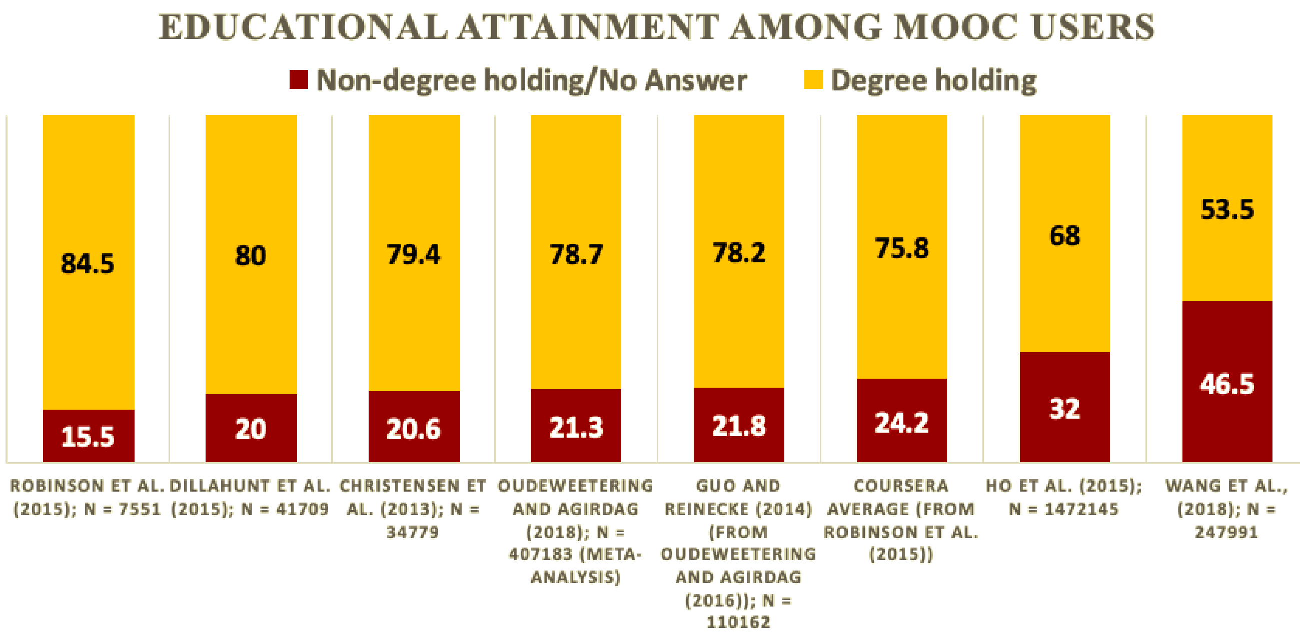


Figure 4.6: Educational Attainment among MOOC Users. More prepared, lower-need learners make up most users in data analysed by the learning analytics research community. This data drives iteration and optimisation recommendations to course design. From Meaney and Fikes, 2019.

Demographic variables are often included in various prediction models based on MOOC data, but the observed impact of demographic variables is inconsistent (Joksimović et al., 2018). However, the way in which demographic variables are considered in prediction models does not necessarily provide insight into whether behaviour, engagement, or course feature patterns, and those corresponding relationships to achievement outcomes, are different across subgroups. Furthermore, analysing the behaviour of underrepresented learners, or even considering the proportions of underrepresented learners across different subpopulations of MOOCs, is an area in need of more research (Li and Baker, 2018). Additionally, Dillahunt et al. (2014) and Zhenghao et al. (2015) do report underrepresented learners enrolling for more practical, professional development and education-oriented reasons. It would be worthwhile to study these segments specifically, disaggregated from the rest, to determine how to potentially iterate future designs based on their needs. Additionally, evidence from Kizilcec et al. (2017) shows that some specific interventions do have heterogenous effects on populations of underrepresented learners, particularly improving course performance for learners expected to experience social identity threat.

Roger’s notion that early-adopters are likely to be advantaged in various ways not only finds empirical support in the existing MOOC data, it also has theoretical support from Knowledge Gap and Digital Divide Theory. Tichenor, Donohue, and Olien (1970) noted that advantaged populations are likely to acquire information about new technologies faster, driving the knowledge gap between more advantaged and less advantaged groups wider. Digital networks function similarly to analogue networks in that a certain level of homophily is expected to be observed (Boyd, 2010). That is, existing users are likely to promote products to their own networks, which are more likely to be demographically similar than different. Furthermore, as noted by Literat (2015), while many of the cost barriers of MOOCs are initially pushed aside, the fee to certify still represents a cost that may create barriers for underrepresented groups.

Finally, while more research into MOOC producers has been consistently called for (Papathoma, 2019), one area that is seriously underexamined is user acquisition strategies. These are the strategies that platforms and service providers implement to acquire new users. Understanding the way MOOC providers and universities pursue this would be a rich area for future research.

Scaling low-barrier, individualised learning experiences that can reach traditionally underrepresented populations or other high-need students requires not only new marketing strategies, but also content and pedagogy designed to suit the needs of these students. Analysing data and deriving insights biased toward the majority of existing users may actually undermine this aim.

4.5.2.2.2 Research-Praxis Bias

Research-praxis bias compounds the potential problems from early-adopter iteration bias, in two separate but interrelated ways. The first source of research-praxis bias is straightforward: practitioners who utilise the insights of the learning analytics community potentially embed conclusions derived from skewed data privileging behaviour patterns of educationally advantaged learners into the course design. One challenge in understanding the extent to which this is the case, however, is related to the second source of research-praxis bias: the noted chasm between research and practice in the development of virtual learning experiences (Price et al., 2016; Bakharia et al., 2016). This chasm plays out in myriad ways.

First, there is generally little research into understanding the roles and perspectives of MOOC producers. This has been noted in several literature reviews (Deng and Benckendorff, 2017; Veletsianos and Shepherdson, 2016; Gašević et al., 2014), and while such work has been increasingly common (Iniesto, 2020; Papathoma, 2019; Lowenthal et al., 2018), it still represents a valuable area of research for the field to explore. Second, there is a significant orchestration problem facing the learning analytics and virtual learning experiences production community (Prieto, Rodríguez-Tirana, Martínez-Maldonado, Dimitriadis, and Gašević, 2019). The learning analytics ecosystem is diffuse and complex. Data sets from multiple sources in different structures and formats represent the richness of data available. However, as noted in a recent review of the literature regarding data integration procedures in learning analytics, only a few of those sources are utilised (Samuelsen, Chen, and Wasson, 2019). Furthermore, there is little detail about how such data sets are integrated and wrangled. Each data integration represents the possibility of learners being dropped and observations omitted. Finally, there is a lack of stakeholder engagement in the learning analytic process, with instructors and course designers often not being involved in research studies (Samuelsen et al., 2019).

These challenges reflect calls by researchers to close the gap between evidence and practice (Ferguson and Clow, 2017) and to develop more human-centred practices for disseminating learning analytic insights in useful, user-friendly ways (Buckingham Shum, Ferguson, and Martínez-Maldonado, 2019). Determining how to better disseminate research insights in a constructive and actionable way to the practitioner community is an important goal for the learning analytics research community moving forward. Additionally, it seems that the learning analytics research community might consider some of the perspectives of practitioners themselves and create a more reciprocal work arrangement. Practitioners in the fields of inclusive education, for example, could help guide learning analytics researchers to more intentionally sub-group and disaggregate data and to note when groups might be marginalised. This approach could help ensure that specific learning needs of certain populations of users are not obscured by the averaged insights produced by big data (Meaney and Fikes, 2019). It is important to note, however, that the divide cuts both ways: the learning analytics and research community has much to offer the practitioner community in terms of specific insights and observations regarding student behaviour derived from data, and the practitioner community has much to offer in terms of knowledge of learning theory, technology development, and differentiated teaching strategies for subgroups of learners.

The meso level of hegemonic design bias hypothesises that, despite the good intentions and noble efforts of researchers and practitioners, certain biases may have unintentionally made the challenge of serving less prepared, higher-need learners more difficult. Early-adopter iteration bias may skew learning analytics and research toward recommendations that optimise course design for more prepared, lower-need learners. Research-praxis bias prevents the broader virtual learning experience production community from fully utilising the insights derived from learning analytics and research properly.

4.5.2.3 Micro Level: Learning Design in Virtual Learning Experiences

The micro level of hegemonic design bias is defined by two crucial shortcomings: the pedagogy and instructional design of MOOCs, as well as the actual course content provided by MOOCs. Considered together, these two design functions fall under the umbrella of what scholars call learning design, which describes the process of creating new practices, activities, plans, resources, and tools aimed at helping students achieve academically (Mor and Craft, 2012).

Learning design is a rich and complicated field, predisposed to generating sophisticated frameworks seeking to disaggregate various components of learning processes into sequences of experiences that can be engineered to facilitate learning. This is a complex process in the analogue world. In the digital world, those complexities are carried over and multiplied by the technological dimension.

MOOCs have generated considerable interest from scholars interested in learning design, which has yielded manifold frameworks for how to produce successful courses. Kauffman and Kauffman (2015) produced a 5C model. Conole (2013) produced a 7C model. Lackner, Kopp, and Ebner (2014) produced a 71-part criteria for quality MOOC design, while Yousef, Chatti, Schroeder, and Wosnitza (2014) produced a 74-part criteria. In a synthesis of these models and more, Sergis, Sampson, and Pelliccione (2017) propose an Educational Design Considerations Framework (EDCF) for xMOOCs, which includes 55 dimensions, based on the established ADDIE framework (Analysis, Design, Develop, Implement, and Evaluate). For each design shortcoming discussed at the micro level of hegemonic design bias, an adapted version of the EDCF framework will be included to exemplify potential remedies to the problems identified. The guidelines provide succinct, clear principles for enabling a course experience that works in opposition to the shortcomings of MOOCs' behaviouralist, non-scaffolded, high self-regulatory and digital literacy requirements, and is thus more inclusive to a broad demographic of learners. An example of the ECDF framework is depicted in **Figure 4.7**.

ADDIE Phase	Phase Element	xMOOC Characteristic	EDCF Guideline	Existing Works
Analysis	A1. Educational problem identification	CCC5a	EDCF 4: The educational problem should be designed in order to be relevant (or adaptable to) to a wide range of cultural contexts	Lackner et al. (2014)
		MCC2b	EDCF 5: The educational problem should be designed as an overarching progressing narrative offering potential side-tracks to follow	-
		MCC4b	EDCF 6: The educational problem should be specific and oriented at engaging participants with problem-solving tasks (i.e., not topic-oriented)	Read and Rodrigo (2014); Margaryan et al. (2015)

Figure 4.7: An example of guidelines from the Educational Design Consideration Framework (EDCF). The ECDF can help guide the design of MOOCs to be more inclusive. Adapted from Sergis et al., 2017.

One shortcoming of MOOCs is that an explicit target audience was never enunciated, beyond broad appeals to "education for anyone, anywhere" (Coursera, 2021). To that end, the focus of my analysis on the learning design of MOOCs will centre on non-college-educated users in the USA, people who are poised to suffer the most from the skills-biased technology change discussed earlier in **Section 4.3.1**, and who could benefit significantly from the flexible learning models afforded by MOOCs. My focus on pedagogy and instructional design, as well as content, is informed by the report from the Brookings Institution, Realism about Reskilling, which proposed a user-centric design model for continuing adult education informed by qualitative interviews with low-wage American workers and experts from the adult learning and workforce development field (Escobari et al., 2019).

Because my focus is on these users, considerations of culture-specific dimensions of pedagogy are not included. Additionally, the question of literal access to technology (see Rohs and Ganz, 2015) and designing for disability (see Iniesto, 2020) are excluded, both to reduce scope and because these questions are the focus of entire literatures themselves. Excluding these factors is both a limitation of hegemonic design bias, as well as potential fodder for its defence; that is to say, while hegemonic design bias for the purposes of this chapter is limited to exploring the use-case of non-tertiary educated learners in the USA, its salience as a framework may well extend into other areas.

4.5.2.3.1 Pedagogy and Instructional Design

The first dimension of hegemonic design bias at the micro level is manifest in the pedagogy and instructional design of MOOCs.

In an analysis of the instructional design quality of 76 MOOCs, Margaryan et al. (2015) found that, while MOOCs were well-organised overall, they scored poorly on instructional design principles; this included, among other shortcomings, little activation of prior knowledge for learners, few opportunities for knowledge integration, and little differentiation of materials for learners with disparate educational backgrounds. MOOCs rely on traditional behaviouralist pedagogy and provide few opportunities for active learning and collaboration, incorporate limited scaffolding to meet students where they are, and require a high degree of self-regulation and digital literacy to complete successfully. Each of these issues is considered in turn.

4.5.2.3.1.1 Behaviourism: Passive Learning and Limited Social Interaction

Distance learning expert Tony Bates (2012) describes MOOCs as stuck in a "very old and outdated behaviourist pedagogy, relying primarily on information transmission, computer marked assignments and peer assessment," and there is little emphasis on participants engaging meaningfully with content. The behaviourist paradigm requires a high degree of self-direction from the learner and relies on a problematic assumption that everyone deep down has a desire to learn (Knox, 2016).

For students without a tertiary degree, the behaviourist design may exacerbate common challenges. Behaviourist pedagogy leaves little margin for error on the part of the learner, which could lead to a sense of frustration, disempowerment, disinterest, and disengagement, especially if pre-existing knowledge barriers are encountered. These emotions could lead to self-doubt, as well as the onset of social identity threat. Social identity threat is induced from self-doubt arising from negative stereotypes attributed to group identity (Danaher and Crandall, 2008). Adult learners may experience these challenges more acutely, as their identities as learners are already well-developed, may have lingering anxiety of school from when they were younger, and feel lower levels of confidence in their technology skills (Rabourn, BrckaLorenz, and Shoup, 2018; Jameson and Fusco, 2014). The behaviourist, highly organised, knowledge-transmission pedagogical paradigm is not conducive to reducing these challenges for students and may actually make them more acute.

In contrast to the behaviourist approach, a more student-centred, active learning approach may be promising. A pedagogy centred on active learning provides people with the opportunities to engage content through practical tasks. Active learning is especially important for adults, who engage in learning to improve their lives in a much more immediate sense and respond to learning that connects concretely to their lives (Knowles, 1980). While more research on active learning is needed, especially in digital environments, active learning has been found to improve student outcomes in the classroom, especially in STEM (Froyd, 2008), and sometimes dramatically so (Laws, Sokoloff, and Thorton, 1999). There is some evidence that more active learning yields better outcomes in digital education as well. While it is difficult to disentangle the selection effect, a recent study suggests that integrating active learning opportunities into online environments like MOOCs may yield better student outcomes. Wise and Cui (2018) find that participating in discussion forums related to course content is a strong predictor of student engagement and completion; while only 15 percent of students do so, these students are twice as likely to complete the course. Several other papers have found similar results (Gardner and Brooks, 2018).

Strategies abound to promote active learning, including in the online, asynchronous context. Think-pair-share exercises (synchronous or asynchronous), problem-centred learning, cooperative learning, inquiry- and discovery-based learning, among countless others (Escobari et al., 2019; Phillips, 2005), provide ways to make learning more active and engaging. These student-centred strategies prompt learners to reflect on new ideas and figure out how to apply them in real-world contexts. The call for more active learning, including a particular emphasis on more social interaction, has been made repeatedly in the MOOC literature as well (Hew, 2016; Kauffman and Kauffman, 2015; Purser, Towndrow, and Aranguiz, 2013).

The Sergis et al. (2017) EDCF framework highlights specific principles that underlie the value of active learning and help illustrate why traditional, behaviourist-anchored approaches are inadequate. **Figure 4.8** highlights this.

ADDIE Phase	Phase Element	xMOOC Characteristic	EDCF Guideline	Existing Works
Analysis	A1. Educational problem identification	MCC4b	EDCF 6: The educational problem should be specific and oriented at engaging participants with problem-solving tasks (i.e., not topic-oriented)	Read and Rodrigo (2014); Margaryan et al. (2015)
Design	Des2. Selection of teaching approach/strategy	MCC1a OC2	EDCF 16: Learning activities should promote/require communication among the participants	Conole (2013), Rubens et al. (2014)
		MCC4b OC2	EDCF 21: The teaching approach should be relevant to the educational objectives and actively engage the participants in challenging tasks and artifact formulation	Kauffman and Kauffman (2015)

Figure 4.8: EDCF guidelines that promote more active learning. Adapted from Sergis et al., 2017.

4.5.2.3.1.2 Limited Scaffolding

As a result of the behaviourist-anchored, passive learning nature of MOOCs, there is little opportunity to provide learners the support they may need while acquiring new knowledge. In his First Principles of Good Instruction, David Merrill (2002) writes, “It has long been a tenet of education to start where the child is. It is therefore surprising that many instructional products jump immediately into the new material without laying a sufficient foundation for the students” (p. 46). This concept, commonly referred to as scaffolding, builds on Lev Vygotsky’s zone of proximal development theory, which posits that learning takes place when students are pushed to integrate new ideas and material that are just beyond their current ability (Nordlof, 2014). As a result, educators adjust learning activities to match a student’s abilities or to push just beyond them. Scaffolding can inform content, processes, and student outputs (Merrill, 2002), and has the effect of supporting a student initially and then gradually easing the support as the learner develops mastery. In their review of the instructional quality of MOOCs, Margaryan et al. (2015) note:

> … in the early stages learners may need considerable support, as learners progress this support should be gradually taken away, with more control shifted to the learner to help build their independence. (p. 78)

The research on scaffolding in MOOCs is limited, but the need for more scaffolding in MOOCs has been noted (Yousef et al., 2014), and several tools have been developed to scaffold support for students (Gutiérrez-Rojas, Alario-Hoyos, Pérez-Sanagustín, Leony, and Delgado-Kloos, 2014; Vihavainen, Luukkainen, and Kurhila, 2012), though it is not clear that these tools have been widely deployed. Furthermore, scaffolding is another technique that could help reduce frustration, doubt, and social identity threat among underrepresented learners. The Sergis et al. (2017) EDCF framework highlights specific principles that can be used to enhance support and scaffolding in a MOOC. **Figure 4.9** highlights this.

ADDIE Phase	Phase Element	xMOOC Characteristic	EDCF Guideline	Existing Works
Cross phase considerations		CCC5a	EDCF 3: Pre-requisite competences for effective participation should be clearly defined to allow the instructor/designer to build on and exploit the participants' prior competences	Rubens et al. (2014), Margaryan et al. (2015)
Design	Des2. Selection of teaching approach/strategy	MCC2b	EDCF 20: Participants should be allowed to engage with learning activities in a nonlinear, conditional manner (e.g., based on their initial motivation, preferences, and/or competences)	Lackner et al. (2014), Rubens et al. (2014)
	Des2. Selection of teaching approach/strategy	MCC4b	EDCF 31: Assessment activities should be designed with progressing difficulty and level of challenge	-

Figure 4.9: EDCF guidelines promoting scaffolding. Adapted from Sergis et al., 2017.

4.5.2.3.1.3 High Degree of Self-Regulation

Another shortcoming of MOOC pedagogy and instructional design is that they require a high degree of self-regulation to complete. According to Kizilcec, Pérez-Sanagustín, and Maldonado (2016) self-regulation, "can be understood as the ability to control, manage, and plan learning actions and behavioural processes that increase goal attainment" (p. 102). This capacity is particularly needed in the MOOC environment. According to Littlejohn et al. (2016), "Massive open online courses (MOOCs) require individual learners to be able to self-regulate their learning, determining when and how they engage" (p. 40).

While straightforward to define, self-regulation has many dimensions to how it manifests. Pintrich (1990) developed a framework to describe how students use self-regulation strategies during learning, comprised of two parts: a set of cognitive management behaviours, and a set of resource management behaviours. To regulate their cognitive behaviours, students engage in 'cognitive strategies' to help manage their intake, processing, and storage of information, as well as 'metacognitive strategies,' which help them determine tasks and set goals. To regulate their resource management behaviours, students engage in resource management strategies, which help them manage things like date-keeping for assignments (Kizilcec et al., 2016).

This description helps clarify why self-regulation is such an important capacity when taking a MOOC, predicated on behaviourist pedagogy and typically with a lack of scaffolding. Because of the highly diverse audiences that MOOCs can attract, this prerequisite of a high degree of self-regulation presents a significant challenge. Learners are expected to determine their own learning journey, including planning their time and effort and self-monitoring progress, all with minimal interactions with instructors and peers. As a result, a wide range of behaviours are observed (DeBoer, Ho, Stump, and Breslow, 2014). Students that do engage in self-regulated behaviours generally do better in courses (Kizilcec and Schneider, 2015). Furthermore, there is considerable prior work suggesting that interventions that help scaffold and promote self-regulated learning behaviours are effective. And while one-time interventions of self-regulated learning may be insufficient (Kizilcec et al., 2016), more consistent, holistic approaches should be evaluated.

In terms of actual design, there are a number of specific recommendations that MOOCs could incorporate to promote self-regulation among learners. These are codified in the EDCF guidelines represented in **Figure 4.10**. The strategies can be as small as having a progress bar as a feature of the course interface to as involved as calling for rapid and personalised feedback on assessments that inform a learner of their progress and potentially address scaffolding needs.

ADDIE Phase	Phase Element	xMOOC Characteristic	EDCF Guideline	Existing Works
Cross phase considerations		CCC5a	EDCF 3: Pre-requisite competences for effective participation should be clearly defined to allow the instructor/designer to build on and exploit the participants' prior competences	Rubens et al. (2014), Margaryan et al. (2015)
Design	Des3. Selection of assessment method	CCC4a MCC4a	EDCF 24: Regular and/or direct feedback should be provided to the participants, either directly (e.g., by the instructor/tutor) or through their engagement with assessment activities	Guàrdia et al. (2013), Margaryan et al. (2015)
		MCC3a	EDCF 28: Engaging in learning/assessment activities will assign the participants' avatar/profile with points, which can be utilized as a method of assessment of educational objectives' attainment	-
		MCC3b	EDCF 29: Reward mechanisms can be employed in order to acknowledge participants' achievements (e.g., badges)	-
Develop	Dev2. Development or selection of educational tools and/or services	CCC4a MCC4a	EDCF 40: Educational tools that allow for the provision of automatic and/or personalized feedback should be selected	Rosewell and Jansen (2014)
Implement	I1. Delivery	MCC3a	EDCF 46: Mechanisms should be utilized to inform participants on their completion status (e.g., a progress bar)	Yousef et al. (2014b)
		CCC4a MCC4a	EDCF 47: Notification/reminder emails can be sent on a regular interval regarding aspects of the course (e.g., upcoming deadlines, next lesson overviews, or individualized progress reports)	Lackner et al. (2014)
	I2. Monitoring	MCC4b	EDCF 49: Learning analytics mechanisms should be used to identify participants at risk of drop out or high achievers (e.g., through assessment results, level of activity engagement or contributions in discussions)	Yousef et al. (2014b)
Evaluate	E1. Formative evaluation	MCC4a	EDCF 50: Feedback on assessment activities should be provided quickly and inform/scaffold the participant in terms of their specific shortcomings	Yousef et al. (2014b)
		MCC4a	EDCF 51: Formative evaluation results and feedback could be provided using diverse means to signify the participant's progress (e.g., text, badges, or ratings) and allow for self-reflection	Margaryan et al. (2015)

Figure 4.10: EDCF guidelines for promoting self-regulation among learners. Adapted from Sergis et al., 2017.

4.5.2.3.1.4 Digital Literacy Barriers

While not accounted for in the Sergis et al. (2017) framework, digital literacy barriers are important to consider as well. More educated, wealthier Americans feel more comfortable using technology. In contrast, those with lower levels of education utilise technology less in their lives overall, need help using new tech devices, have lower confidence in their computer skills, and are unsure they can find reliable information on the internet (Horrigan, 2016a). Furthermore, lower-income Americans are more likely to be dependent on a mobile device as their sole means to access the internet. A recent study from Pew (2019) found that 71 percent of low-income Americans making less than $30,000 have a smartphone, and it provided a quarter of them with their only source of internet access. Producers of MOOCs should take these concerns into account. Designing welcoming, user-friendly, straightforward user experiences that are mobile-optimised is crucial to provide meaningful opportunities for diverse audiences.

Digital literacy extends beyond just knowing how to navigate a user interface, however. Beyond comfort in use, low digital literacy can also reflect a lack of awareness of new technology concepts in general and of ed-tech specifically (Horrigan, 2016b). This is even more pronounced for digital learning and professional development tools (Horrigan, 2016b). Among Americans with a college degree who report engaging with learning for professional advancement, 64 percent use the internet for at least some of it, compared to 40 percent of those without a college degree. Furthermore, 61 percent of all adults were unfamiliar with distance learning, and 80 percent had little to no awareness of MOOCs (Horrigan, 2016b).

4.5.2.3.2 Content

Beyond the various pedagogical and instructional design concerns highlighted, there are several issues with MOOC content that need to be considered. First, it should be noted that the content of MOOCs is a rather unexplored area of the literature (Babori, Zaid, and Fassi, 2019). Babori et al. (2019), through a systematic literature review, find that while MOOCs cover a massive range of content, the content instructed within a MOOC is rarely the subject of academic research.

What little research there is on this topic does not present a promising picture for including more underrepresented learners. For example, in their 2016 paper on humanities MOOCs and underrepresented students, Evans and McIntyre note a significant gap between how courses are framed for users and what is expected of them. They found that 80 percent of courses listed no previous knowledge requirements aside from English proficiency, but in reality, imposed significant prerequisite knowledge and skill barriers. This phenomenon is illustrated by descriptions such as, 'No background is required; all are welcome!' with later qualifications like, 'No special background is needed other than the willingness and ability to synthesise complex texts and theoretical material' (Evans and McIntire, 2016, p. 318). From a learning design perspective, the questions regarding content can be further specified into two buckets: the complexity of the content itself, as well as the language used to present the content.

4.5.2.3.2.1 Complexity of Content

The complexity of the math and verbal reasoning skills required to engage and succeed in a MOOC should be analysed and considered as a design constraint for MOOC production. In the context of the USA, there is likely a wide gap between the literacy and numeracy skills required to succeed in a MOOC and the capacities of most Americans. According to OECD analysis of recent scores from PIAAC (the Program for the International Assessment of Adult Competencies), one in three adults have low numeracy skills, and one in six have low literacy skills (OECD, 2013). As recently as 2002, it was estimated that close to one in two American adults are unable to accurately complete learning activities requiring higher-level reading and problem-solving skills (NCES, 2002).

These estimates all have problems. They come from different samples from different years. Many need to be updated. When paired with other more recent, more reliable data, including the fact that only 35 percent of Americans have a bachelor's degree or more (NCES, 2017), the idea that a high proportion of adults struggle with lower literacy and numeracy seems plausible. For lower-wage workers, defined as making less than two-thirds the national median wage, adjusted for cost of living, these gaps are likely more acute, given lower educational attainment, as demonstrated in **Figure 4.11**.

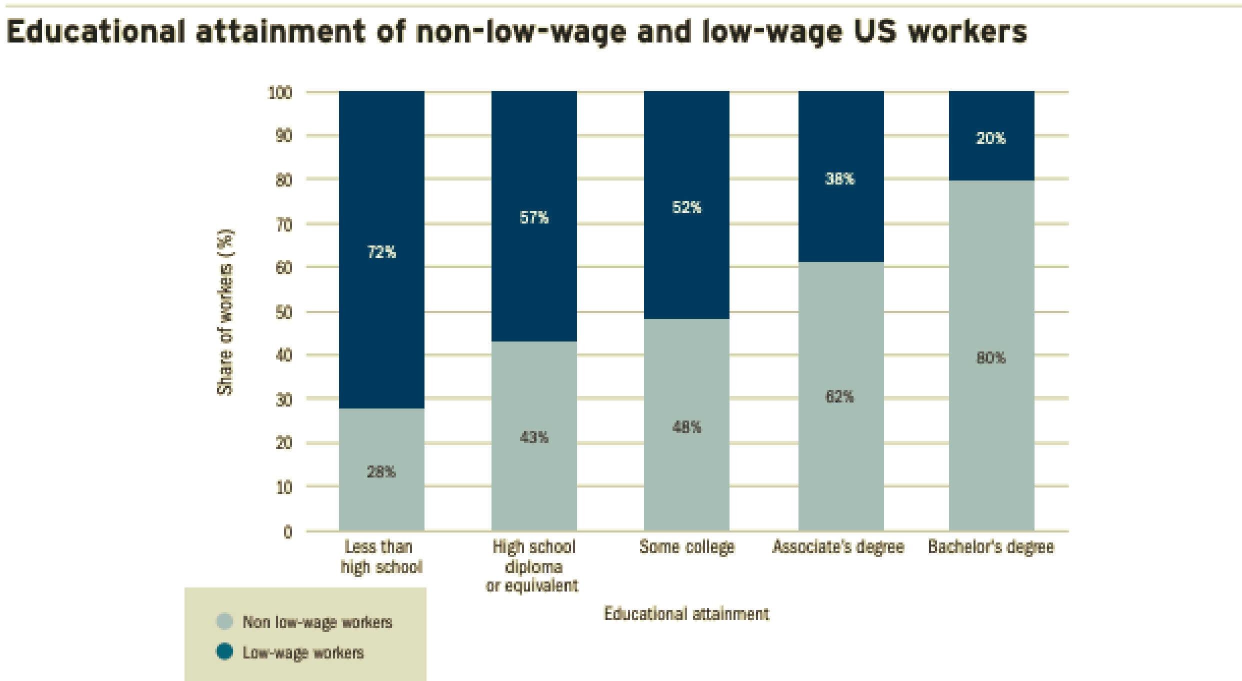


Figure 4.11 Educational attainment of low-wage and non-low-wage workers. From Escobari, Seyal, and Meaney, 2019.

Given this context, when the *Introduction to Data Science* MOOC requires learners to have "intermediate programming experience and some form of familiarity with databases," (Babori et al., 2019, p. 228) the gap in what kinds of learners MOOCs are able to serve, resultant from their content, is apparent.

Specific, evidence based design guidelines from Sergis et al. (2017) take this into account in the EDCF framework, shared in **Figure 4.12.** These principles suggest that MOOC producers specifically define and make clear the prerequisites needed, as well as develop supports and differentiated content for diverse populations of learners.

ADDIE Phase	Phase Element	xMOOC Characteristic	EDCF Guideline	Existing Works
Cross phase considerations		CCC5a	EDCF 3: Pre-requisite competences for effective participation should be clearly defined to allow the instructor/designer to build on and exploit the participants' prior competences	Rubens et al. (2014), Margaryan et al. (2015)
Design	Des1. Definition of Educational Objectives	MCC3c OC1	EDCF 11: Different levels can be defined for the stated educational objectives in order to allow different attainment thresholds for participants with diverse prior competences/motivation/preferences	-

Figure 4.12: EDCF guidelines for providing more accessible content in MOOCs. Adapted from Sergis et al., 2017.

4.5.2.3.2.2 English Dominant

In addition to the complexity of the content, the language of instruction of MOOCs is another design dimension that emerges as a potential barrier for non-college-educated MOOC learners. While hegemonic design bias explicitly excluded cultural considerations so as to focus on the American context, even in the American context, the predominance of English across MOOC platforms is problematic, especially if the intent is to serve traditionally underrepresented populations. Estimates suggest that upwards of 75 percent of MOOC content is in English (Stratton and Grace, 2016).

When considering the low-wage workforce, 62 percent of whom have no tertiary degree, language becomes even more essential to consider. Recent American Community Survey data reports that of the 11.1 million workers in the USA who report speaking English “less than well,” two-thirds of them are low-wage workers (Escobari et al., 2019). About 47 percent of low-wage workers without English proficiency do not have a high school diploma, illustrated in **Figure 4.13**. Low-wage workers who struggle with English are three times less likely to enrol in continuing education as their English-proficient counterparts (Escobari et al., 2019). These numbers further underscore the extent to which supports for English language learners should be taken into consideration for MOOCs, as well as the requisite content calibration based on the expected learning needs of this population.

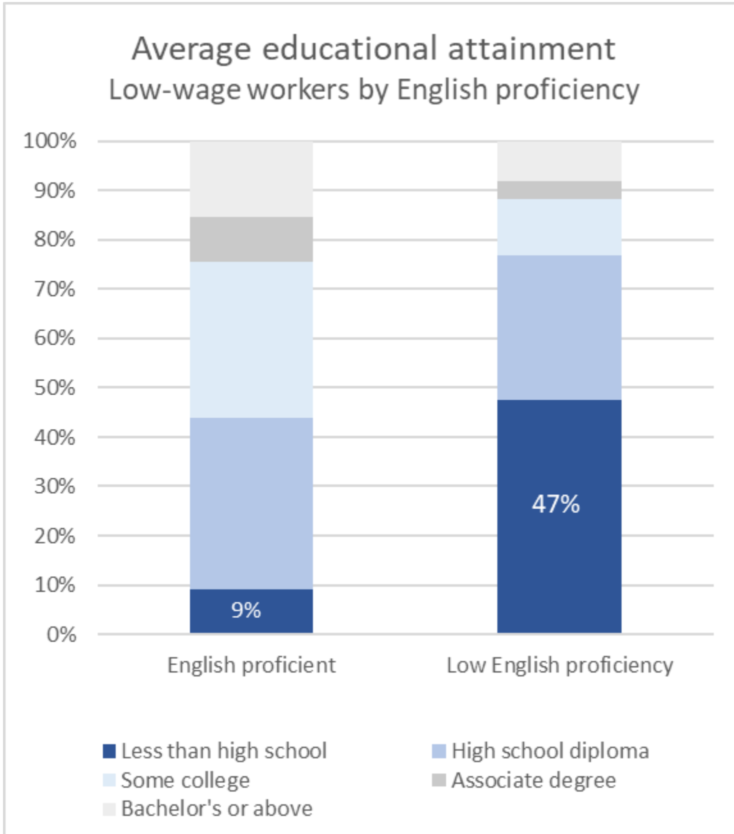


Figure 4.13: Average educational attainment for low-wage workers by English proficiency. From Escobari, Seyal, and Meaney, 2019.

Sergis et al. (2017) take this into account in the EDCF framework, shared in **Figure 4.14**. These principles suggest that MOOC producers take specific steps to consider, and potentially investigate, the cultural backgrounds and language proficiencies of potential learners to inform content design.

ADDIE Phase	Phase Element	xMOOC Characteristic	EDCF Guideline	Existing Works
Cross phase considerations		CCC5a	EDCF 3: Pre-requisite competences for effective participation should be clearly defined to allow the instructor/designer to build on and exploit the participants' prior competences	Rubens et al. (2014), Margaryan et al. (2015)
Analysis	A3. Learner Analysis	OC1 Cross Characteristic	EDCF 8: The xMOOC should gather and exploit participant data related to their cultural background (e.g., language, country of origin, profession, and expertise) and initial motivation for engaging in the course	Kauffman and Kauffman (2015)
Develop	Dev1. Development/selection of educational resources	CCC5a	EDCF 34: Diverse educational resources should be selected in order to meet the local contexts of a wide range of participants	-

Figure 4.14: EDCF guidelines for considering language proficiency among diverse learners. Adapted from Sergis et al., 2017.

4.6 Discussion: Operationalising Hegemonic Design Bias

Having defined hegemonic design bias, I now turn to how this framework might be operationalised and tested in the future. As noted by Gorard (2010), educational research papers, especially of the critical kind, are filled with theories explaining social phenomena. When this is done in an ad hoc manner, however, untethered to a set of scientific principles that allow the claims to be verified, falsified, or explored, the claims evade strict scrutiny. They exist amorphously across the boundaries of disciplines and methods, protected from holistic critique against an objective standard or agreed-upon framework, while simultaneously leaving no discipline or method out of their weaponised kaleidoscope of critique. An entire ontological and epistemological universe has been defined to justify this kind of academic work (Hammersley, 1995b). While often rhetorically persuasive and sometimes emotionally satisfying, it falls into a philosophy of science trap of potentially not only being inaccurate, but also being "not even wrong" (Jung and Pauli, 1960, p. xxxiii). While the claims are provocative, their veracity is difficult, if not impossible, to discern.

Hegemonic design bias seeks to avoid being classified as such. It strives to concretise explicit mechanisms at the various levels operative in distance education that represent real constraints on the institutions and actors designing and building technological artefacts. These constraints and shortcomings include the relative importance of knowledge production to knowledge dissemination within, as well as the exclusionary nature and the institutional isomorphism of, elite American higher education; early-adopter iteration bias and research-praxis bias observable in the technology design and production system; and myriad examples of tactical pedagogical and instructional design, as well as content choices, within MOOC courses. Where applicable and extant, existing studies elucidate and lend credibility to these proposed concepts. Furthermore, at the micro level specifically, the EDCF framework developed by Sergis et al. (2017) provides concrete design considerations that can be made in light of design shortcomings of MOOCs.

To further clarify and substantiate hegemonic design bias, the following sections will attempt to operationalise the concepts outlined. First, I articulate a set of principles and assumptions required to operationalise hegemonic design bias in the context of MOOC design. Then, I frame components of hegemonic design bias as hypotheses that can be iterated upon and tested based on these principles and assumptions.

4.6.1 The Paramount Design Principle: Specifying a Goal

As described repeatedly, dozens of academics have illuminated the failure of MOOCs to democratise learning for the educationally underrepresented. The question remains, however, of how to appropriately understand this failure, if, indeed, MOOCs are to be potentially redesigned to serve as a democratising force for tertiary learning.

One way we can understand MOOC failure is to consider it intentional, and as the result of a planned, colonial exporting of Western knowledge through the insatiable means of technologised capitalism, sheathed in the veneer of promoting global educational equality. Another way to understand it is to frame it as unintentional negligence; that, while the universities producing MOOCs may have been well-intentioned, they were institutionally and culturally constrained from delivering their goal, a sad but all-too-common case of charitable discourse masking a well-intentioned failure. Another way to see all of this might be to suggest that the attempt itself was half-baked; that, like many features of the modern, bureaucratised, information economy, MOOCs were pursued in haphazard and ad hoc ways, in a competitive race for prestige and novelty, during which many of the design challenges of building technology for underrepresented learners were not adequately considered.

These three potential considerations can be thought of as a set of broad hypotheses. Gathering data about them, while potentially difficult, especially regarding the first intentional, oppressive claim (as one imagines very few administrators would admit to such a scheme), is nonetheless possible. And, indeed, more data about the MOOC design processes is needed, as this remains a relatively unexplored part of the literature.

That said, hegemonic design bias encompasses a series of hypotheses predicated on the latter two considerations: unintentional negligence and haphazard design processes. It is important to state these hypotheses explicitly. Not doing so leaves hegemonic design bias, or any potential theory regarding the shortcoming of MOOCs, open to the criticism of straw-manning; that is, constructing a distorted claim, and then proceeding to dismantle that claim, all the while leaving open the possibility that the original distortion of the claim is indeed that which allows the claim to be dismantled (Hansen, 2020). Some of the more critical claims regarding MOOCs may fall into this trap.

For any scientific claim to be verified, some metric must be established against which progress toward a clearly articulated goal can be measured. It is not clear that a primary audience for MOOCs was ever explicitly articulated. Instead, appeals to democratisation and inclusion were perhaps narrative rather than substantive (Rohs and Ganz, 2015). If MOOCs were to have met this original ideal, an ideal end user for the project would need to be developed, and the notion of inclusion measured by the extent to which this end user's learning needs were met. It is far from clear that this explicit articulation was ever made. Rather than a retrospective observation, this criticism holds true today. The homepage of Coursera.com reads, "World-class learning for anyone, anywhere" (Coursera, 2021). The "about" page on edX.org states their mission to be, "Increase access to high-quality education for everyone, everywhere" (edX, 2021).

This is not to say that MOOCs should inherently be limited to some particular group. On the contrary, part of their initial appeal was that they were open to everyone. Nonetheless, some median user or set of users must serve as the archetype toward which to design. It is not surprising that, in the case of the major MOOC providers, this archetypal user seems to be similar to the archetypal user found on an elite American college campus, with high levels of academic proficiency in reading comprehension and mathematics, digital literacy, and self-regulation. However, research on 'fit for purpose' MOOCs that have specified a particular, underrepresented audience, and were intentionally designed for that audience, indicates that these approaches can and do work (Lambert, 2020; King et al., 2014).

Establishing a clear goal is central to the design of any system (Rittel and Webber, 1973). Indeed, as Crow and Dabars (2015) write, "identifying the objective discloses the novel design challenge" (p. 248). Educational technologies are no different, as Zawacki-Richter et al. (2018) note:

> In order to produce effective learning experiences with quality learning materials, the analysis of learner characteristics and profiles is the starting point in the instructional design process. (p. 250)

To that end, operationalising hegemonic design bias will centre on non-tertiary-educated users in the USA; more specifically, the median American adult with no college degree, who, according to OECD, struggles to read critically and do mathematics in a sophisticated way. These populations are poised to suffer the most from the skills-biased technology change discussed earlier, and they could benefit significantly from the flexible learning models afforded by MOOCs. As was revealed in **Section 4.5.2.3**, this population overlaps substantially with lower-wage workers. Against this specific backdrop, hegemonic design bias, along with other MOOC theories and research, can be evaluated.

4.6.2 Macro Level: Who is Producing MOOCs, and for Whom?

The key claim of hegemonic design bias at the macro level is that elite universities in the USA are unlikely, because of institutional constraints and cultures, to be able to produce MOOCs that serve underrepresented learners. At the same time, these are the most well-resourced educational institutions in the USA (NCES, 2020), so it is conceivable that, if they took their own biases into account and invested resources into building technologies that actually reach underrepresented learners in the

USA, or hired the right people to help them do so, they perhaps could. If an elite university took on such a charge, the following hypothesis could be operationalised.

- Hypothesis 1: Elite universities, when specifying their intended audience explicitly and designing for this audience, can build MOOCs and similar virtual learning experiences that facilitate the academic progression and achievement of underrepresented learners; specifically, those without a tertiary degree.

At the other end of the spectrum are colleges and universities that have demonstrated a capacity to serve underrepresented learners well. Indeed, Chetty et al. (2017) identified a host of tertiary education providers that do serve learners from significantly underrepresented backgrounds effectively. These include schools like Cal State University, Los Angeles; State University of New York, Stony Brook, and the University of Texas, El Paso. While these universities and others like them would likely need support to make such an investment, they may be able to translate their success in analogue tertiary education for underrepresented students into success in the digital realm, and the following hypothesis could be operationalised.

- Hypothesis 2: Non-elite colleges and universities, which already demonstrate some capacity and ability to serve traditionally underrepresented learners, could leverage their insights and build MOOCs and similar virtual learning experiences that facilitate the academic progression and achievement of underrepresented learners; specifically, those without a tertiary degree.

4.6.3 Meso Level: The Educational Technology Design and Production System

The meso level of hegemonic design bias proposes that well-educated learners are biasing data in learning analytic evaluations of MOOCs and similar virtual learning experiences through a process called early-adopter iteration bias. There are some considerable difficulties in testing this hypothesis. One such difficulty is that the highly educated users are so overrepresented in enrolment. This makes disaggregating data difficult because sample sizes between groups of advantaged versus underrepresented users are so different. This becomes more difficult when analysing behaviours deeper along the participation funnel during a MOOC, where expected attrition and differentiated behaviour shrink samples even further. Mechanisms for intentionally recruiting underrepresented learners into MOOCs might be a potential way to mitigate these composition and attrition challenges.

Additionally, while an underexplored area in the research literature (Samuelsen et al., 2019), wrangling data across multiple platforms in an environment where demographic data on users is already sparse is difficult and poses challenges. At the same time, one aspect of the MOOC environment that does make these kinds of analyses potentially possible is that, despite the composition and attrition issues, it is possible that the sample sizes remain large enough to detect effects. All that said, once appropriate mitigation strategies or analytical methods that could adequately address these issues are determined, the following hypothesis could be tested:

- Hypothesis 1: Motivations for course enrolment, utilisation of course features, and the relationships between these and academic outcomes are heterogenous across different population segments, especially educational background status.

More disaggregated, intentional exploration of non-mainstream or underrepresented MOOC users would help advance the field (Gardner and Brooks, 2018; Deng et al., 2017) and could test parts of early-adopter iteration bias.

The second component of the meso level of hegemonic design bias is research-praxis bias, which contends that learning analytic research, in theory used for practice, is biased toward well-educated users. Even more problematic, however, is the inadequate relationship between the practitioner and research communities, preventing even the potentially biased insights from informing MOOC design, but also preventing valid insights, and insights from other parts of the academy, from informing the design and development of MOOCs.

The research on MOOC producers is limited and an area for improvement in the literature. This is especially true for literature that seeks to understand the design processes for underrepresented groups that producers may be considering. Additionally, general calls for making learning analytic insights translate to actual learning design improvements have been made consistently in the past few years (Buckingham Shum et al., 2019; Ferguson and Clow, 2017).

One potential way to operationalise research-praxis bias would be to conduct a set of qualitative explorations of MOOC producers receiving specific professional development on designing MOOCs based on the research literature. There are myriad other survey and observation tools that could measure whether MOOC practitioners feel more equipped and better able to do their job if some mechanisms were in place to benefit from the academic community studying MOOCs and similar virtual learning experiences.

To truly operationalise this kind of hypothesis would require substantial effort. One such method for doing so could be through a quasi-experimental approach. A university could leverage past data on MOOC enrolment, behaviour, and achievement, and subsequent data after some trial intervention that exposes designers in a legitimate way to the insights of learning analytics. This type of experiment could be especially interesting if the insights were disaggregated and specified for underrepresented learners.

- Hypothesis 2: After implementing a robust professional development plan for MOOC producers, which exposes them to state-of-the-art learning analytic and design research on how to better meet the needs of learners without a tertiary degree, enrolment, persistence, and achievement increases for learners without a tertiary degree are observed.
- Hypothesis 3: Learning analytic dashboards of attrition funnels, disaggregated by education background, can lead to targeted, timely interventions that over time raise the persistence of non-tertiary educated learners.

4.6.4 Micro Level: MOOC Pedagogy and Instructional Design, and Content

The micro level of hegemonic design bias posed a series of issues with the pedagogy and instructional design of MOOCs, as well as with the content. A number of quite fruitful hypotheses could examine these issues by considering and implementing the EDCF framework developed by Sergis et al. (2017), which comprises a set of 55 specific recommendations that can enable inclusive design for MOOCs. In the realm of pedagogy specifically, where there is already ample research to consider for how to create virtual learning experiences aligned with the needs of diverse learners, seeking to make courses more interactive and less behaviourist is a good place to start. Measuring the specific engagement patterns and outcomes associated with these types of implementations could yield insight into how to best design courses for underrepresented learners. Such hypotheses might encompass the following:

- Hypothesis 1: Through implementing a light, asynchronous, virtual think-pair-share exercise which asks learners to demonstrate understanding of early course content, measured engagement is higher across all learners, including learners without a tertiary degree.

- Hypothesis 2: Adding a "connection to the real world" sequential to each course chapter leads to observable engagement increases among learners without a tertiary degree.
- Hypotheses 3: Building a high-quality "College Algebra for Everyone" math MOOC would attract a larger proportion of underrepresented learners, who would persist at higher rates than in traditional MOOCs on more sophisticated content.

These three examples build off the existing literature as well as best practices from adult learning theory. Hypothesis one incorporates an active learning exercise that engages students in applying newly acquired knowledge in a non-threatening manner, building off the insight that engagement in course discussion boards is associated with increased achievement (Wise and Cui, 2018). Hypothesis two incorporates a core tenet of adult learning theory, which holds that adults are more likely to engage in learning when it is relevant to their lives (Rabourn et al., 2018; Knowles, 1980). Hypothesis three reflects the reality that at least one-third of American adults are likely to need remedial math courses (OECD, 2013).

4.7 Conclusions

This chapter set out to frame MOOCs and their shortcomings in the context of skills-biased technology change. With this framing, the chapter then turned to the specific research questions.

RQ1: What dynamics of the distance education ecosystem enable or constrain institutions of higher education in the provision of MOOCs and similar virtual learning experiences for underrepresented learners?

- **RQ1.1 What research methods and theoretical concepts help explore and propose a framework accounting for such dynamics, while adhering generally to a subtle realist research orientation?**
- **RQ1.2 What would such a framework entail, and what existing MOOC literature lends evidence to it?**
- **RQ1.3 How might that framework be operationalised and tested?**

Regarding question **RQ1.1.,** a post-positivist (Phillips, 1990), subtle realist (Hammersley, 1992) theory-building research method (Kettley, 2010) enabled the construction of a conceptual framework, utilising a variety of different theories and concepts across a multidisciplinary literature. These included the analytical lens from social informatics, Socio-technical Interaction Networks (Meyer, 2006), the insights from Langdon Winner's (1980) explication of the politics of technology, as well as Everett Roger's (2010) theory on the diffusion of innovations.

The methods and concepts identified in research question one then enabled the construction and exploration of the conceptual framework, hegemonic design bias, helping answer **RQ1.2.** This framework describes bias and constraints in the macro, meso, and micro levels of distance education that constrain institutions of higher education in the provision of inclusive MOOCs and similar virtual learning experiences for underrepresented learners. At the macro level, elite higher education in the USA is constrained by a relative valuing of knowledge production over knowledge dissemination; admissions procedures yielding small groups of easy to teach, elite students; and institutional isomorphism, leading other universities toward elite mimicry.

At the meso level, homophily among early-adopting MOOC users, particularly in that they are disproportionately highly educated, has potentially biased learning analytics to make recommendations for how to optimise course design for already-advantaged learners. This may bleed into research-praxis bias, whereby practitioners use analysis biased toward well-educated learners to improve course design. However, it is unclear the extent to which MOOC producers themselves are even that connected to the learning analytics and research community. So, while the early-adopter bias of learning analytics itself may be avoided, this comes at the risk of a broader disconnect between the research and practitioner community that is sub-optimal.

Finally, at the micro level of course design, a series of design choices reflective of behaviourist pedagogy, a lack of scaffolding, and a requirement of high levels of self-regulation and high levels of digital literacy all potentially make MOOCs an unwelcome and challenging environment for underrepresented learners without a tertiary education. Similarly, the sophisticated content, both in terms of actual information presented, and in English fluency, do not consider the reality of non-tertiary educated Americans, many of whom struggle with literacy, numeracy, and English fluency.

A number of concrete hypotheses that help operationalise these insights were also reviewed, helping answer **RQ1.3.** It is likely that support from the public and social sector would be required to set out such an ambitious scope of work for the research and development communities of MOOCs. If MOOCs are to ever live up to their initially democratising aims, however, such a coordinated and focused investment may be required.

4.7.1 Limitations

There are a number of limitations to this chapter. First, the product of this research effort is a set of hypotheses to test the veracity of a conceptual framework. Future research will be required to determine the validity and reliability of this framework. Second, the multidisciplinary range of research considered is all connected to deeper bodies of evidence that may have provided further insight into the claims being developed. These insights should be further investigated and leveraged to strengthen the conceptual development.

5 ADDING A DEMOGRAPHIC LENS TO CLUSTER ANALYSIS OF PARTICIPANTS IN ENTRY-LEVEL MOOCS

All really good research does is generate new hypotheses.
– David Goldberg

5.1 Chapter Overview

Section 5.2 introduces the motivating issues and research approach to this chapter and summary findings. **Section 5.3** provides an overview of the literature investigating usage patterns and learner outcomes in MOOCs, concluding with attention to the limited insight we have about these issues regarding underrepresented learners. **Section 5.4** defines the specific questions this chapter seeks to address, and methods and data used to investigate these questions. Some limitations with these approaches will be noted and considered further in the conclusion. **Section 5.5** presents the results of two cluster analyses. First, I explore a common clustering approach utilising performance and participation data, based on Manhattan Distance measures and the CLARA clustering algorithm, later enriched by consideration of education level subgroups. Next, I leverage Gower Distance measures and the PAM clustering algorithm, which allows for categorical variables like education level to be included in distance measurement. The second set of clusters are enriched by consideration of SES subgroups in the USA. **Section 5.6** discusses the implications of these results, and **Section 5.7** concludes with a discussion of why this is relevant to building more inclusive MOOCs, as well as a discussion of the limitations of this chapter.

5.2 Introduction

COVID-19 catalysed a boom in online learning (Dhawan, 2020). This brought renewed attention to the digital divides that amplify existing educational inequalities between students from high-SES backgrounds and those from lesser means (Bozkurt et al., 2020). According to Pew, in the context of the USA, nearly 95 percent of parents reported that their children's schools were shut because of the pandemic (Vogels, Perrin, Rainie, and Anderson, 2020). About one-fifth of parents expressed concern that their children would not be able to complete schoolwork because of inadequate access to a computer at home or would have to use public Wi-Fi because home internet was unreliable. Close to one-third of parents reported that it was somewhat likely their children would need to complete schoolwork on a cell phone. These challenges were especially acute among parents with low incomes, 43 percent of whom reported that their children would likely need to complete schoolwork on a cell phone, 40 percent of whom reported that their children would need to use public Wi-Fi, and 36 percent of whom cited a lack of access to a computer at home as likely preventing their children from completing their schoolwork (Vogels et al., 2020).

These digital access gaps, while deeply troubling, are descriptive of a first-order digital divide; that is, the differential access to technologies among populations along the socioeconomic spectrum (Van Dijk, 2017). These gaps may point to, but do not account for, differences in usage patterns of technologies among different groups, differences that may further exacerbate the inequalities that technology may have been developed to help solve (Warschauer and Matuchniak, 2010).

Since the 1990s, scholars have articulated a deeper conception of the digital divide, moving beyond questions of access to questions about how technology is used and the associated outcomes of using it (Van Dijk, 2013; Van Dijk and Hacker, 2003). These usage patterns and the outcomes they mediate are informed by the design of the technologies themselves, the design and production ecosystems, as well as how these components interact with a person's social, cultural, and economic capital (Kvasny, 2002). Put another way, access itself to technology is insufficient; instead, access to technology should be understood in a larger context of social, cultural, and economic factors that help determine if that access is meaningful. A focus on access itself, without attending to the complementary resources and interventions needed to help facilitate technology utilisation by diverse populations, does little good. In the absence of such resources and interventions, resolving first-order digital divides by equalising access gives way to the more pernicious second-order digital divide of inequality of usage (Van Dijk, 2017). This is true of educational technology; as Selwyn, Gorard, and Furlong (2006) note, digital education resources:

> …appear to be reinforcing rather than activating processes of self-education, allowing people to continue with pre-existing and pre-set patterns of informal learning which generally replicate and reinforce patterns of 'offline' self-education. (p. 141)

As described in **Chapter 4** on hegemonic design bias, understanding potential heterogeneous behaviour patterns of demographic subgroups of users remains an underexplored area of the MOOCs literature (Gardner and Brooks, 2018; Deng et al., 2017). Furthermore, the development of complementary resources and interventions to enable meaningful technology utilisation across different groups is vital if MOOCs are to help democratise learning. The first steps toward doing so involve understanding not only differential access patterns, which have been well-documented (Reich and Ruipérez-Valiente, 2019; Rohs and Ganz, 2015), but determining whether differential usage patterns exist as well.

Investigating behaviour patterns of MOOC users is central to the existing literature (Joksimović, Kovanović, and Dawson, 2019; Joksimović et al., 2018). Impressive work by the learning analytics community has mined massive data sets to track and model student behaviour patterns and outcomes in MOOCs. This literature has produced novel, interdisciplinary insights and has documented extensively the extent to which MOOCs reflect existing first-order digital divide issues (Reich and Ruipérez-Valiente, 2019; Rohs and Ganz, 2015). Additionally, cluster analysis and other analytics methods have been used to understand different behaviour patterns of subgroups within MOOCs (Li and Baker, 2018; Ferguson and Clow, 2015; Kizilcec, Piech, and Schneider, 2013). Less attention has been paid to considering whether and how these behavioural subgroups differ across demographic characteristics, particularly demographics revealing dimensions of underrepresented status like educational background and SES.

In seeking to contribute to our understanding of these areas, this chapter focuses on leveraging a common method of computationally intensive data analysis on a previously unexamined set of data from entry-level tertiary MOOCs offered by a large, research-intensive university in the USA. Leveraging an initial dataset of more than 260,000 students, and a subset of 29,000 'committed learners,' I cluster analyse MOOC participants based on their performance and participation. The clusters are enriched by considering how learners with different education backgrounds are dispersed throughout. A second, less common method of cluster analysis is then used, which explicitly considers education background in computing distance measures. Additionally, data on median household income from the 2016 American Community Survey, at the Census tract level, is matched to a subset of users to further investigate the clustering profiles of users based on approximated SES. Analysing SES is not common in MOOC studies because of the sparse demographic data in MOOC environments. My approach follows Ganelin and Chuang (2019) by pairing geolocated zip code data to Census tract estimates.

The analysis generated several notable results. The clustering approach yielded the same four to five clusters commonly observed in the research literature (Li and Baker, 2018; Kizilcec et al., 2013). Learners without a college degree, however, were found more likely to be successful than their better-educated peers; additionally, learners from low-SES backgrounds were found to perform just as well as peers from high-SES backgrounds.

As specified in **Section 1.6.1** and **Section 2.2.1** comments about MOOCs more generally in this chapter refer to Coursera- and edX-style xMOOCs produced in the USA predominantly in English, and which stipulate open enrolment without entry qualifications, have no barriers to access content (though the content may be copyrighted and thus not meet the 'open' definition of OER), are online and available to anybody with an internet connection, and are free to complete though may charge a fee for certification (Deng et al., 2019). The data analysed in this chapter comes from edX MOOCs, and is further discussed in **Section 5.4.5.**

5.3 Literature Review

This literature review considers how learning analytics, broadly speaking, have been used to investigate learner behaviour in MOOCs. I then examine how cluster analysis has been used in the extant MOOC literature, followed by what we know about engagement patterns of underrepresented learners using MOOCs.

5.3.1 MOOCs and Their Characteristics

The digital nature of MOOCs makes them distinct from traditional learning environments, especially regarding the signals that can be analysed to draw conclusions about the relationships between student behaviour and academic outcomes. While the analogue education world is rich in demographic data and other kinds of categorical variables about learners, the behavioural and engagement data is sparse. MOOCs, meanwhile, produce rich behavioural and engagement data, but provide little insight into the characteristics of their students (Gardner and Brooks, 2018). This is, in part, because data on student intention and background characteristics is sparse in MOOCs. Little mandatory data is collected, so low response rate questionnaires are often the only instruments that can help inform these variables for analysis.

Other features of MOOCs also differentiate them from other educational environments, particularly in that they are internet-based courses open for enrolment to anyone, with low stakes, unlike traditional higher education where courses are taken for expensive credit coupled with penalties for poor performance (Gardner and Brooks, 2018). These features combine to attract heterogenous participants to enrol, varying significantly across intention in taking the course, educational background, country of origin, and familiarity with the content (Glass, Shiokawa-Baklan, and Saltarelli, 2016).

While the participants are heterogenous and data on them is limited, some common characteristics are frequently observed. Most users are located outside the USA and hold a bachelor's degree (Reich and Ruipérez-Valiente, 2019; Rohs and Ganz, 2015). Some 90 percent of enrolees do not complete their courses (Jordan, 2014). In a typical university environment these learners would be considered dropouts, but this conceptualisation is grounded in more traditional educational contexts that may not be adequate for MOOCs (DeBoer et al., 2014), so Reich (2014) proposes that stop-outs may be more appropriate.

5.3.2 Learning Analytics and Methods

Two related but distinct fields have emerged to study big data in education: educational data mining (EDM) and learning analytics (LA) (Ferguson, 2012). EDM is more focused on automated discovery and the implications for software development. EDM is prominent in designing and building automated tutoring platforms and personalised learning engines. There is somewhat less emphasis on the human judgement required to make sense of data, and EDM is less concerned about the overall learning ecosystems in which these technologies are produced and operate (Siemens and Baker, 2012). LA leverages many of the same analytical tools as EDM, though with a slightly different lens and purpose. LA focuses more on the interaction of learners with technology, and whether and how this produces learning. LA is focused on leveraging the large amount of data resultant from digital environments, paired with computationally intensive techniques and models grounded firmly in learning theory, to discover insights on how to optimise learning (Ferguson, 2012).

In theory, these insights would then be used to inform learners in real-time of their progress, or be used by the practitioners building the virtual courses, in what Clow (2012) has conceptualised as the learning analytic cycle. Translating insights into practice, however, has posed challenges for LA, some of which were noted in **Section 4.5.2.2** at the meso level of hegemonic design bias. This is especially true insofar as high-quality LA insights from academia struggle to be translated into improved pedagogy and design among practitioners building educational technologies (Ferguson and Clow, 2017). Researchers have called for LA to integrate more methods from human-computer interaction, including consideration of usability, user experience, and interaction design, in the hope of further closing the research-practice gap in the learning analytic cycle (Buckingham Shum et al., 2019). Because I am interested in the design and practice of building MOOCs, and how that relates to learning for people, I locate my work on the LA side of the spectrum, and the remainder of this literature review will focus primarily on work from that domain.

The major analytic tools used in LA are prediction methods, relationship mining, and discovery with models, all with the emphasis of empowering teachers and learners (Siemens and Baker, 2012). These methods help relate the independent or explanatory variables to the dependent or outcome variables. These variables are almost always some combination of student achievement label or score as the dependent or outcome variable, and a variety of dimensions or features that are hypothesised to relate to that label or outcome as the independent or explanatory variables. The central focus of these analyses is to understand whether and how students learn during virtual learning experiences by seeking to establish a relationship between a tangible outcome (e.g., student achievement label or score) and some set of variables influencing that outcome, such as engagement data. As noted previously, MOOC data can be incredibly rich with measurements of these variables, and might include measurements of total event logs, patterns of video watching, types of engagement with forum discussions, and frequency of syllabus access, just to name a few.

Cleaning, integrating, and managing this kind of data requires considerable expertise along a steep learning curve and is riddled with technical and ethical issues (Katal, Wazid, and Goudar, 2013; Jacobs, 2009). These complexities, especially as they relate to digital education and LA, are generally under-researched in the literature, and can impose barriers to advancing the field (Samuelsen et al., 2019).

These barriers and how they specifically relate to my project are considered in the methods and limitations sections of this chapter.

These complexities notwithstanding, LA methods have been leveraged to help improve adaptive tutoring systems, personalised intervention systems (Baker, 2016), early-warning alert systems (Brooks, Thompson, and Teasley, 2015), and enhance predictive modelling (Gardner and Brooks, 2018). Researchers have also investigated the deployment of interventions at scale to improve student completion (Kizilcec et al., 2020).

Beyond these pursuits, analysing different subgroups of students has emerged as a central way of researching MOOCs through LA methods. Ho et al. (2015) analysed over 800,000 student registrations in the first 17 courses offered by edX. They group learners into four categories: only registered, or users who enrolled but never accessed the courseware; only viewed, or users who engaged with less than half the available chapters; only explored, or users who engaged with more than half the material but did not certify; and certified, or users who earned a certificate. DeBoer et al. (2014) draw on data from 150,000 students, including some 230 million clickstream events, to explore MOOC usage. They report that of the more than 150,000 who enrolled, only 70 percent registered at least one click event, half watched a lecture video, 20 percent attempted a homework assignment, and 8 percent posted in a discussion forum. From these results, DeBoer et al. (2014) suggest a reconceptualisation of traditional educational variables is needed in the MOOC context.

Moving beyond categorisation, researchers have analysed the specific behaviour patterns of subgroups of learners. Guo and Reinecke (2014) analysed over 140,000 students in four edX MOOCs and found that certificate earners skipped 22 percent of the course content, and frequently employed non-linear navigation strategies. Anderson, Huttenlocher, Kleinberg, and Leskovec (2014) grouped MOOC participants on two variables, video watching and assignment taking. The analysis was based on data from six Coursera courses containing a total of more than 320,000 students. The researchers found five prototypical engagement patterns. 'Viewers' primarily watched lectures and rarely turned in assignments. 'Solvers' watched few lectures but handed in assignments for a grade. 'All-rounders' balanced watching lectures and handing in assignments. 'Collectors' downloaded lectures and handed in few assignments. 'Bystanders' registered for a course, but total activity was below a low threshold.

5.3.3 Cluster Analysing Patterns of Engagement in MOOCs

One of the most common methods deployed to investigate the relationship between student behaviour patterns and outcomes in MOOCs is cluster analysis. Cluster analysis has been described, simply, as “the art of finding groups in data” (Kaufman and Rousseeuw, 2009, p. 1).

Humans have long sought to classify and categorise things. To a certain extent, this is a subjective process of discerning and assigning patterns of similarities and differences to objects and assigning those objects to groups based on these observations. Computational techniques over the past half-century have helped establish more robust and objective processes, which is especially important as more and more data is considered (Kaufman and Rousseeuw, 2009). Cluster analysis relies on algorithms that iteratively measure and classify similarities or differences between observations on an indefinite number of parameters. The way that these similarities or differences are measured, known as distance measures, is crucial, and will be considered further in the methods section. One of the most common methods employed in cluster analysis is the K-means algorithm, which seeks to assign observations in a data set to K-number of clusters. K-means iteratively builds clusters around cluster centroids, seeking to minimise the distance between each observation and the centroid of its assigned cluster (Huberty, Jordan, and Brandt, 2005).

Researchers have leveraged cluster methods, and K-means particularly, to explore a variety of different questions in both cMOOCs and xMOOCs contexts. While results of clustering can be leveraged for other kinds of modelling, like prediction, the primary purpose of cluster analysis is exploratory, typically utilised to understand and explore which subgroup populations map on to various kinds of behaviour patterns. Though papers in this stream of the academic literature do sometimes comment on the differences in the demographic make-up of the clusters, education level is only sometimes considered and SES even less so.

Kizilcec et al. (2013) use K-means to cluster analyse more than 90,000 learners enrolled in three computer science MOOCs. They determine four prototypical user types: completing, auditing, disengaging, and sampling. These users are defined by steep drop-out points and deeply unequal levels of participation. Completing learners finish most of the assessments, although with varying degrees of mastery. This trajectory is most reminiscent of how students progress through traditional classes. Auditing learners complete assessments infrequently but engage with the course through watching video lectures throughout the majority of the course. Disengaging learners complete assessments at the beginning of the course but at some point disengage, usually in the first third of the class. Sampling learners usually engage with only one video in the course, typically at the beginning of the course.

The methodology employed by Kizilcec et al. (2013) has been leveraged across several different MOOC environments. Ferguson and Clow (2015) leveraged an augmented version of the Kizilcec et al. (2013) methodology on four FutureLearn courses from roughly 35,000 learners, using K-means but computing distance with Euclidian Distance instead of Manhattan. It is notable that the FutureLearn platform utilises a more social learning, cMOOC-like approach. Ferguson and Clow (2015) suggest that the differences in course structure may be why the augmented methods were required. They identify seven clusters of student engagement. First, 'samplers' who visited, but only briefly; this was the largest cluster. Second, 'strong starters,' who completed the first assessment of the course, but then dropped off sharply. The third group, 'returners,' started strong and completed the first assessment, returned and took the second assessment, but then dropped out. Cluster 4, 'midway dropouts,' completed nearly half the assignments before dropping out. The fifth group, the 'nearly there,' completed most of the assignments but dropped out just before the course ended. Cluster six, 'late completers,' completed the final assessment and most of the other assessments but were either late or missed some. Finally, cluster seven, 'keen completers,' completed the course diligently and engaged actively throughout. The proportions of these learners were relatively consistent across MOOCs, with steep drop-offs followed by unequal levels of participation.

When courses were disaggregated, Ferguson and Clow (2015) found three supplementary clusters. The first came from MOOC 2 in the study. The midway dropouts were not observed in this course; instead, an ambiguous cluster that accounted for 13 percent of the learners was observed. These learners typically submitted the first assignment, often tardy, and visited the MOOC regularly and left comments. The next two supplementary clusters came from MOOC 3. This course only had three assessments and so did not contain students in the returning or midway dropout clusters. The first supplementary cluster from MOOC 3 in the study was 'samplers-who-comment;' these learners accounted for twenty percent of the population and looked much like samplers; they frequently submitted the first assignment, visited only briefly, but all left comments. The second supplementary cluster in MOOC 3 in the study was quite small, representing only two percent of students. These students all submitted the final assessment but did not engage consistently beforehand. These results may indicate it is important to consider the course length and structure when seeking to generalise clusters across multiple courses.

Ferguson led another team of researchers in 2015 to conduct a similar study that examined data from 32,000 learners in five FutureLearn MOOCs offered by four universities (Ferguson et al., 2015). They found that the seven clusters observed in the original study were observed in MOOCs that used similar assessment patterns and ran for seven or eight weeks. The seven clusters were not found on the MOOCs that only ran for three weeks, or on the MOOC that did not include assessment. The authors summarised this finding succinctly, stating, “Learners did not work through a three-week MOOC in the same ways that learners work through the first three weeks of an eight-week MOOC” (Ferguson et al., 2015, p. 1).

Chen, Håklev, Harrison, Najafi, and Rolheiser (2015) analysed data from an initial sample of more than 300,000 students enrolled in six courses from a Canadian university. They utilised slightly different methods than K-means, defining user behaviour by the sums of clicks into forums, lectures, wikis, and quizzes, and then applied hierarchical clustering. They observed students clustering into five groups. The first group was ‘all-rounders,’ who were active participants across all behavioural dimensions. The second and fourth clusters were similar to all-rounders, but had less engagement overall, and were thus labelled ‘all-round-less,’ and ‘each-bit.’ The third cluster was characterised as ‘active quiz takers.’ The fifth group engaged with some course material, but did not take quizzes, and were labelled ‘casual learners.’

Kovanović et al. (2016) cluster analysed 26,025 students who enrolled in at least two courses (a total of 52,050 course enrolments) in eleven different courses offered by the University of Edinburgh on Coursera. The researchers leveraged K-means clustering, standardised their classification variables prior to analysis to control for differences in course offerings, and removed students who merely enrolled in the course. They found five clusters: students who only enrolled, students with low engagement, highly engaged students who watched videos and took quizzes, students who engaged mainly by watching videos, and a small percentage of students who put an emphasis on online discussions.

Khalil and Ebner (2017) utilise K-means clustering with Euclidian Distance measures to evaluate learners on the iMOOX platform based in Austria. Clusters were derived from students' engagement on quizzes, videos, and discussion forums. They found four engagement patterns. 'Registrants' were students who enrolled in a course but did not engage with it at all. 'Active learners' were students who took some action, like watching a video or taking one quiz. 'Completers' were students who successfully completed all quizzes but were not certified. Finally, 'certified students' completed the course and were certified by the platform.

Arora, Goel, Sabitha, and Mehrotra (2017) investigated a data set of more than 600,000 learners from sixteen courses offered by MIT and Harvard. K-means clustering was leveraged based on interactions with the course material, discussion forums, and assessment. Five clusters were identified: 'uninterested,' 'casuals,' 'performers,' 'explorers,' and 'achievers.' Researchers then mapped these clusters onto surface, deep, and strategic learning approaches. These clusters followed similar patterns found in previous literature. Casual learners were less active, explored less content, and did not perform well; uninterested learners were the least active and had negligible performance; the performers cluster performed well but with less effort and engagement; explorers seemed more interested in the course content than in performing well, with moderate levels of engagement but low performance; finally, achievers were the group of learners that were highly engaged and performed well.

Kahan, Soffer, and Nachmais (2017) conduct a similar analysis seeking to characterise different types of participant subgroups in MOOCs by analysing a database of over 20,000 learners from one Coursera MOOC. They utilise hierarchical clustering to analyse the participant behaviour based on engagement with video lectures, discussion forums, and assessments. This led to 7 different clusters emerging: 'tasters,' 'downloaders,' 'disengagers,' 'offline engagers,' 'online engagers,' 'moderately social engagers,' and 'social engagers.'

While qualitative work on MOOCs remains an area to improve upon in the literature, there is some qualitative work that has clustered groups of MOOC students into distinct behaviour patterns. Milligan et al. (2013) analyse 29 interviews with students from a cMOOC to determine engagement patterns . They found learners to be grouped into 'active,' 'passive,' and 'lurking.' Active learners were actively engaged with the course material and maintained blogs and a Twitter presence, which enabled them to interact with other learners. Lurking learners followed along in the course but were not actively engaged. Finally, passive learners were frustrated and not satisfied with the course.

While the Ferguson and Clow (2015), Ferguson et al. (2015), and Kahan et al. (2017) papers diverged from the original set of clusters observed by Kizilcec et al. (2013), the remaining papers consistently report roughly four types of engagement patterns that emerged in the data. These four categories of students are confirmed in the literature beyond research using strictly cluster analysis as well (Anderson et al., 2014; Ramesh, Goldwasser, Huang, Daume, and Getoor, 2014). As described by Li and Baker (2018), these behavioural engagement groups are sometimes labelled with different names, and sometimes a group may be split into a fifth group or combined into a third, but the prototypical engagement patterns remain the same, and broadly speaking can be classified as: 'disengagers,' 'auditors,' 'quiz-takers,' and 'all-rounders.' 'Disengagers' enrol in the course but have very little engagement thereafter; these participants have also been called 'tasters', and 'bystanders,' and these students typically made up the largest sub-group. Auditors engage with the course material and video, but rarely submit assignments; these participants have also been called 'viewers' and 'casual students.' 'Quiz-takers' engage less with the course materials and content, but complete and submit assignments; these participants have been called 'solvers' and 'performers.' All-rounders are students who engage most similarly to conscientious students in traditional courses, with high levels of interaction with course materials and assignment submissions; these participants have also been called 'completing students' and 'achievers' (Li and Baker, 2018).

5.3.4 Cluster Subpopulation Characteristics

Gardner and Brooks (2018) note why the unique characteristics of MOOCs justify developing predictive models distinct from traditional educational environments. Whereas traditional analogue educational environments are rich in demographic data but sparser in behavioural data, MOOCs suffer from the opposite problem. This means that, while a robust literature has developed around analysing student behaviour in MOOCs, progress in understanding questions about behaviour patterns potentially differentiated along demographic lines is more limited. Another problem is that learning analytic strategies often focus on average relationships between achievement and behaviour, which may obscure important heterogeneity among subgroups (Li and Baker, 2018), and described at the meso level of hegemonic design bias in **Section 4.5.2.2**. This potentially holds for the demographic characteristics of subgroups as well.

Determining the type of heterogeneity to track is itself complicated. Li and Baker (2018) investigated behavioural and cognitive engagement in an analysis of three math MOOCs with over 70,000 learners. They found that engagement differentially predicted achievement across the four commonly observed learner subgroups of disengagers, auditors, quiz-takers, and all-rounders. While these results do not delve into differential behaviour patterns and outcomes along SES and educational background, they do point to nuanced heterogeneity within clusters, which may help identify important indicators for at-risk participants within subgroups.

Some of the existing research leveraging cluster analysis to understand learner behaviour and engagement in MOOCs does report differences in demographics (or intentions, and other categorical variables, when the data exists, e.g., Kizilcec et al., 2013). Because of the sparse data of MOOCs, however, much of this reporting is dependent on user-opt in surveys, which biases the results significantly. Furthermore, educational background level and SES are not often examined. Nevertheless, there are still some demographic findings to note.

Kizilcec et al. (2013) note that males are more widely represented than females in two of three courses they analyse, though no significant differences in cluster representation emerge; additionally, as human development index at the country level increases, so too did completing and disengaging learners, while the proportion of sampling learners decreased. The authors note that, regarding employment status, "…in all courses, learners on different engagement trajectories are approximately equally distributed within the three most represented employment statuses: working full-time, graduate and undergraduate student" (Kizilcec et al., 2013, p. 5). Khalil and Ebner (2017) found that quiz-takers were more likely than other groups to be enrolled in an undergraduate program. Kahan et al. (2017) found that the social engagers were, on average, older and less likely to be working. Tasters and downloaders, on the other hand, were more likely to be working. Regarding intention, Chen et al. (2015) find that there are significant differences between subgroups' reported intentions and behaviour in the course, with those who enrol for academic reasons more likely to be quiz takers and users who enrol for fun more likely to be all-rounders.

These are useful insights. However, it is striking that there are few if any studies examining whether and how different kinds of engagement patterns exist along underrepresented dimensions. The focus on broadening representation within higher education to include underrepresented groups has been central to education policy for decades (Crow and Dabars, 2015). The narrative of MOOCs fit well within this push. When the empirical data suggested MOOCs were struggling to support increasing college enrolment for underrepresented learners, MOOCs seemed to have pivoted (Reich and Ruipérez-Valiente, 2019), instead of seeking to better understand whether, how, and why diverse, underrepresented populations of learners were using MOOC platforms. These kinds of insights could help inform MOOC design and potentially contribute to higher levels of underrepresented student enrolment and success in the future. Recent work has also demonstrated that MOOCs can help promote and improve educational outcomes for diverse learners when designed intentionally to meet the needs of underrepresented populations, oftentimes through the courseware itself or through hybrid program partnerships with community groups (Lambert, 2020). Much of this work, however, is considered "an alternative global practice that exists alongside more commercial MOOC offerings" (Lambert, 2020, p. 144), and was derived from qualitative work that, while producing valuable insights, is uncertain to scale.

5.3.5 What Do We Know About Underrepresented Learners in MOOCs?

A more robust literature emerges considering underrepresented learners and MOOCs when the lens broadens beyond studying user behaviour and engagement patterns through cluster analysis. Some of this literature was reviewed in **Section 2.3** and **Section 4.3**, so what follows will be a summarised version. The literature is focused on two considerations. First, enrolments; from the earliest papers on MOOC enrolments, it has been noted repeatedly that most learners already have a tertiary degree (Ho et al., 2015; Emanuel, 2013). Second, intentions; while subject to considerable selection bias, surveys have been deployed across a range of contexts which have revealed information about why underrepresented groups are participating in MOOCs; in particular, that underrepresented learners are more likely to pursue MOOCs for professional advancement (Zhenghao et al., 2015; Dillahunt et al., 2014).

These insights are based primarily on enrolment data or survey data, are descriptive, and provide little insight into the specific behaviour patterns of these groups, and whether and how they may differ from other groups. Nevertheless, a number of papers have shed insight into why underrepresented learners are using MOOCs and are worth mentioning.

First, before doing so, it is worth restating explicitly the dimensions of underrepresentation I am interested in exploring: the representation of students without a tertiary degree, and the representation of students from lower SES backgrounds; these dimensions are further specified in **Section 1.6**. There are several other dimensions of underrepresentation to consider. Indeed, questions regarding dis/ability, gender, the human development index of a country, access to technological resources, and many others all represent very worthy variables to consider. As articulated in the chapter on hegemonic design bias however, my interest relates particularly to how MOOCs might provide educational opportunities that can serve as a means to economic mobility, especially in the context of skills-biased technology change. Education level, insofar as it represents a proxy for capacity for higher-skilled work, and SES, insofar as it represents a proxy for the opportunity for further economic attainment, make sense in this context. Furthermore, in the analogue and traditional online education worlds, both variables have been extensively considered and understood to be factors that influence a student's capacity to succeed (Rizvi, Rienties, and Khoja, 2019; APA, 2017; Jaggars, 2014).

5.3.6 Prior Educational Attainment and MOOC Completion

The evidence on the relationship between education level and MOOC participation is mixed and incomplete, and there is no consensus (Joksimović et al., 2018), with some finding no relationship (Brooks et al., 2015), and others finding that more highly educated learners are more likely to persist (Kizilcec and Halawa, 2015).

For example, there are papers that have found non-tertiary educated learners to persist at lower rates. Engle, Mankoff, and Carbrey (2015) examine the data of more than 30,000 students, 15,000 of whom responded to the pre-course survey, in an introduction to physiology MOOC on Coursera. They find that completion and certification rates are positively associated with educational background, noting "students with graduate degrees were more likely to pass the course or pass with distinction than students with only some college experience or a bachelor's degree" (Engle et al., 2015, p. 46). The quite apparent pattern is reproduced below in **Figure 5.1**, which shows a smaller and smaller fraction of lower-educated learners persisting in the course. This replicates a finding of Guo and Reinecke (2014), who analysed over 140,000 students in four edX MOOCs, and found that nearly 70 percent of students who completed a certificate held a bachelor's or master's degree. Greene, Oswald, and Pomerantz (2015) analysed more than 30,000 students who took a Coursera MOOC and similarly found that higher levels of previous education were associated with less dropout.

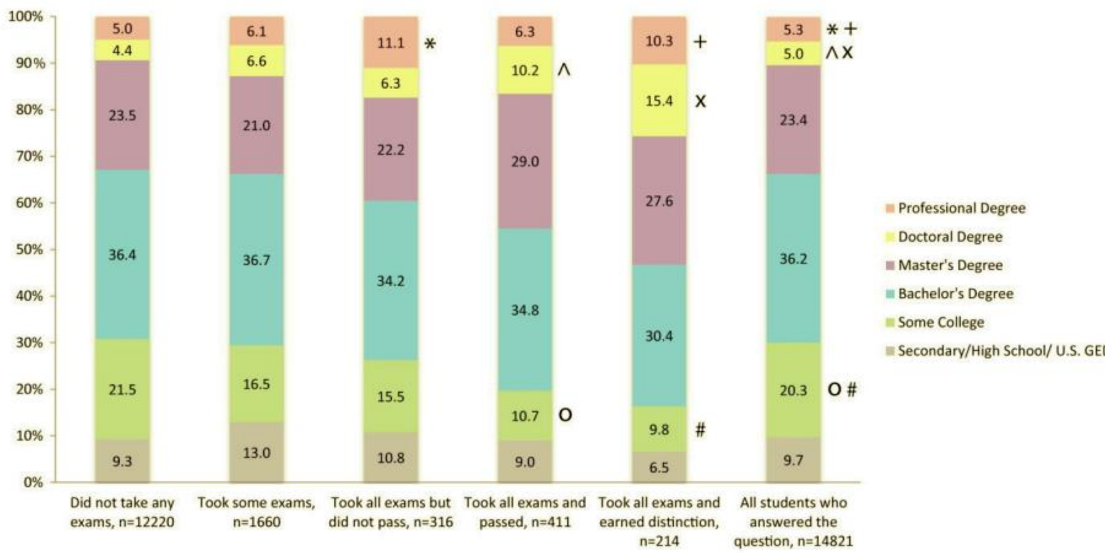


Figure 5.1: A funnel of MOOC participation disaggregated by education level, indicating disproportionate attrition of learners without a tertiary degree. From Engle et al., 2015.

Others have found no association between prior level of educational attainment and outcome. Zhang, Bonafini, Lockee, Jablokow, and Hu (2019) conducted a study to explore demographics and student motivation as predictors of completion of MOOCs. They analysed survey data of 655 participants in one MOOC. Their regression models showed no significant effect of students' educational background on course completion. Goldberg et al. (2015) studied some 10,000 enrolees taking an *Understanding Dementia* MOOC that was intentionally designed to accommodate the needs of underrepresented learners and found no relationship between prior educational attainment and student outcomes. The instructional design intentionally allowed for more time for students to engage with the material, more flexibility, and opportunities to retake exams. This is a significant finding, as the authors note:

> Participants with education levels that ranged from primary (elementary) school to vocational training were as likely to complete this MOOC as participants with associate, undergraduate, and postgraduate university degrees. This is an important and previously un-reported finding. It supports the intent of MOOC developers to be inclusive and offer learning opportunities to students from diverse educational backgrounds to equip them for further university study. (Goldberg et al., 2015, p. 5)

Other types of analyses on specific MOOC designs for underrepresented learners have other potentially important implications. Wang, Fikes, and Pettyjohn (2018) examine the effects of education level and country of origin on course completion and college-earning credit in a series of entry-level MOOCs. Their analysis is constrained to a segment of ‘committed learners,’ defined as students who did not drop the courses, i.e., those who attempted an assessment after the ID-verification date (equivalent to the add-drop date). They find that lower education level learners were represented at a higher rate and perform better than in more traditional MOOC offerings.

5.3.7 Socioeconomic Status and MOOC Completion

Less work has been done to understand the relationship between SES and MOOC participation. This is partly due to the difficulty of collecting SES data in the context of MOOCs. Two primary methods have been used to do so, the first being through survey research, and the second by matching a learner’s self-reported address or geolocation to Census data to understand where the user may approximately fall on the socioeconomic spectrum. In general, the findings suggest that success in MOOCs is biased toward those from high-SES backgrounds, but that there may be interesting differences in motivations for enrolment between high-SES and low-SES groups.

Hansen and Reich (2015), matching self-reported mailing addresses to Census data, found that the average MOOC user was more likely to live in wealthier and more highly educated neighbourhoods. They note that learners from high-SES backgrounds were more likely to complete a certificate. A recent paper by Ganelin and Chuang (2019) analyses 76,000 user registrations for edX courses between 2012 and 2018, identifying the location of enrolees by both geolocation and user-reported mailing address.

They find that registration rates are higher among prosperous postal codes. They also find that IP geolocation data makes errors geographically and economically by disproportionately placing users in prosperous areas, underestimating the regressive nature of enrolment.

Despite MOOCs mostly serving learners from more educated and wealthy backgrounds, however, there is some evidence that learners from more disadvantaged backgrounds are using MOOCs to seek professional advancement (Stich and Reeves, 2017; Zhenghao et al., 2015; Dillahunt et al., 2014).

5.3.8 Literature Review Synthesis and Opportunities to Contribute to the Literature

Several conclusions can be drawn from this literature review. The first two are related to clustering and demographics of MOOC participants themselves, and the third relates to bias that may exist in MOOC data that, while not a prominent feature of the existing literature, can be reasonably deduced.

First, data mining techniques, particularly clustering methods, seem a reasonable way to approach analysing engagement across learners in MOOCs. There are some nuances regarding the best way to do so; specifically, selecting the best clustering technique, best features to consider, and the best algorithms and distance computation metrics to include, which will be discussed further in the methods sections. Second, while some insight has been shed into how clustered subgroups of MOOC users are comprised of different demographic characteristics, there is an opportunity to enrich this literature by leveraging these types of methods with a lens toward identifying differential demographic assortment along the lines of education level and SES.

Third, while it is not a prominent feature in the literature, the academic level of many of the courses included in existing analysis is unclear. Many seem to be based on analysis of upper-level undergraduate or graduate courses, though relating the content offered by MOOCs to student engagement and outcomes is a noted area of need in the literature (Babori et al., 2019). This could bias the data and insights, so it will be fruitful to see if entry-level MOOCs attract a different population of learners and if these learners behave differently, as observed by Wang et al. (2018) and Goldberg et al. (2015).

5.4 Research Methodology and Context

This section details the quantitative analysis in this chapter. First, I briefly comment on how conducting this kind of research fits within my ontological approach. Next, I consider the research questions, which are derived from the literature. Then, I detail the methods utilised, laying out the exploratory cluster analysis processes I followed. I then detail the research context, ethics, and data.

5.4.1 Brief Comment on Ontology

As developed in **Section 2.6**, the multimethod (Hunter and Brewer, 2015), post-positivist (Phillips, 1990), subtle realist (Hammersley, 1992) approach to research pursued in this thesis values the utilisation of empirical data, both qualitative and quantitative, to help improve our understanding of reality, while accepting the limits to our capacity of objectively doing so. STIN (Meyer, 2006) was introduced in hegemonic design bias as a framework to help balance the social and technical aspects in technology development. Perrotta and Williamson (2018) utilise a similar, though more relativist framework called Actor-Network Theory (Latour, 1996) in an article exploring the subjective, human dimensions of cluster analysis. Cluster analysis relies on several determinations by the researcher in which certain variables and outcomes are deemed important and assigned certain meaning, while others may not be. Concurrently, the decisions that researchers make themselves are not made in isolation of social and institutional considerations, including what data is available to them.

This is a helpful framing for my own cluster analysis. I believe cluster analysis can help provide insight into how certain subgroups of users are performing and engaging in courses. On the other hand, a limitation of my own cluster analysis is that a variety of personal, social, and institutional forces shaped the data I was able to analyse, and thus ultimately the data I selected to analyse, which in turn informed the distance measures and algorithms I utilised for my analysis. So, while this is an empirical exploration, it is laden with subjective, human decisions that shape the analysis.

5.4.2 Research Questions

The literature is ambiguous regarding the relationship between student demographic characteristics and MOOC engagement and outcomes (Joksimović et al., 2018). At the same time, researchers have leveraged cluster analysis to explore different engagement and achievement patterns in MOOCs (Ferguson and Clow, 2015; Kizilcec et al., 2013). Furthermore, there is a need to better understand non-mainstream users of MOOCs (Deng et al., 2017) and whether different subgroups of students indicate heterogenous engagement and achievement patterns (Gardner and Brooks, 2018). Based on this reading of the literature, I sought to replicate existing versions of cluster analyses and explore demographic subgroups within these clusters with a particular focus on underrepresented learners, and to do so in a context of explicitly entry-level MOOCs. I thus crafted my research questions as follows:

- **RQ2: How are traditionally underrepresented students engaging with MOOCs?**
    - **RQ2.1: Do learners in entry-level tertiary MOOCs demonstrate similar patterns of clustering found in the broader MOOC literature?**
    - **RQ2.2: Are demographic subgroups of learners, specifically along the educational background dimension, represented equally across clusters?**
    - **RQ2.3: What demographic and engagement insights can be unveiled through leveraging a more novel, demographically-sensitive cluster analysis method?**

5.4.3 Research Methods

Implementing cluster analysis methods involved careful consideration of data features to include, which distance measurements between those features to compute, as well as selection of a clustering algorithm to group data into clusters based on those distance measurements (Kassambara, 2017; Kaufman and Rousseeuw, 2009). After experimenting with more than 30 different combinations of variables, distance measures, and algorithms, I settled on presenting two sets of exploratory cluster analyses to help answer the research questions. The analysis and results in **Section 5.5** present the findings, which follow the methods described in this section.

The first analysis presented follows a more traditional form of cluster analysis discussed in the MOOCs literature. First, I compute a Manhattan Distance (Loohach and Garg, 2012) matrix based on total grade and a composite performance and participation metric (defined further below). After assessing the clusterability of the data, I verify the ideal number of clusters utilising the silhouette method (Kassambara, 2017) and the gap statistic method (Tibshirani, Walther, and Hastie, 2001). Next, the data is clustered using the CLARA algorithm (Kaufman and Rousseeuw, 2009). Finally, traditional data analytic methods are used to evaluate the engagement patterns and the demographic make-up of the clusters, specifically level of educational attainment.

The second cluster analysis is broadly similar but utilises a third dimension on which to cluster the data: educational background. Utilising a categorical variable alongside standard interval variables is an uncommon approach with MOOCs data. Doing so requires a different distance metric, Gower Distance (Gower, 1971), and more limited verification methods; namely, the gap statistic method cannot be used. The silhouette method (Kassambara, 2017) is utilised again to determine the ideal number of clusters. The PAM algorithm (Kaufman and Rousseeuw, 2009) is then used to cluster the data, and then traditional data analytic methods are used to evaluate the engagement patterns and the demographic make-up of the clusters, with a particular focus on approximated SES.

5.4.3.1 Approach to Cluster Analysis

There is no linear process to cluster analysis. Determining a distance measure to compute is dependent on the type of data available to cluster. Computing distances between observations across features is required to evaluate potential clusterability. If clusterability is determined, the selection of an algorithm depends on the distance measure computed, as well as whether that algorithm has corresponding software in a statistical learning package that enables it to derive clusters based on the distance measures selected. It is an interdependent process. There are a few commonly important steps, however, which are detailed by Kassambara (2017) and Kaufman and Rousseeuw (2009) and discussed below.

5.4.3.1.1 Selecting a Distance Measure

A distance measure computes the distance and similarity or dissimilarity between observations. Different data types have different scales, and certain distance measures are only able to compute distances between certain kinds of data.

The first cluster analysis leverages Manhattan Distances (Loohach and Garg, 2012), a method used commonly in the learning analytic literature (Kravvaris, Kermanidis, and Ntanis, 2016). Manhattan distance sums the absolute differences between observations across features, and requires interval data (Kassambara, 2017; Kaufman and Rousseeuw, 2009). Percent grade and a composite participation and performance metric are both interval observations between zero and one. Manhattan Distance is also referred to as the L1 norm. Kizilcec et al. (2013) used Manhattan Distances in their original cluster paper.

The second cluster analysis leverages Gower Distance. Gower Distance measures the similarity of observations across both numerical and categorical data (Ebbert and Dutke, 2020; Gower, 1971). Gower Distance measures the Manhattan Distances across interval data in a data set, and computes a Dice Coefficient across nominal data by first converting nominal variables of *k* categories into binary columns. Leveraging Gower Distance allows for cluster analysis based on a distinct metric computed on percent grade, the composite participation and performance, as well as educational background.

Distance measures were computed in R (Team R, 2019), utilising the programming packages 'distances' (Savje, 2019) and 'cluster' (Maechler, 2019).

5.4.3.1.2 Assessing Cluster Tendency

Clustering algorithms will find clusters in data arbitrarily if programmed to do so (Kassambara, 2017). Therefore, it is important to determine whether data is clusterable. One of the first ways of doing so is to take guidance from the existing literature, in which discovering clusters of learners is prominent (Li and Baker, 2018; Ferguson et al., 2015; Kizilcec, 2013). Second, several analytical methods exist to measure relative dissimilarity across a data set. One of the most prominent is the Visual Assessment of Clustering Tendency, or VAT, which produces an ordered dissimilarity matrix (Kassambara, 2017). Ordered dissimilarity matrices will be evaluated in my analysis as a potential indication of clusterability. These visualisations give some idea of how clusterable the data is by counting the number of dark-squared blocks along the diagonal axis (Kassambara, 2017), indicating distinct clusters. VAT is utilised for both cluster analysis explorations. VAT was implemented in R, utilising the programming packages, 'nbclust' (Charrad, Ghazzali, Boiteau, Niknafs, and Charrad, 2014), and 'factoextra' (Kassambara and Mundt, 2017).

5.4.3.1.3 Determine Optimal Number of Clusters

Once determining the data is clusterable, or potentially clusterable, it is important to determine the number of clusters to explore. One common method is to evaluate the relative silhouette widths of various potential clusters to determine the best fit-value (Ferguson et al., 2015). Silhouette widths are an internal validation metric that measures how similar an observation is to its own cluster compared to its closest neighbouring cluster (Martin, 2016). A Silhouette width close to 1 indicates the object is well-clustered. A silhouette width close to -1 indicates the object is poorly clustered (Kassambara, 2017). Another common method is the gap statistic method from Tibshirani et al. (2001). The gap statistic computes the total within intra-cluster variation for different numbers of clusters and compares this to the expected values of the total within intra-cluster variation of a null reference distribution of the data. The ideal number of clusters is estimated to be the value that maximises the gap statistic; that is, the point at which the clustered structure is the furthest away from the random uniform distribution of points (Tibshirani et al., 2001).

Silhouette width analysis is utilised for both cluster analyses. The gap statistic method is not optimised for Gower Distance, as it requires numeric variable inputs, and therefore is not utilised for the second set of analyses.

R packages utilised for these implementations included 'cluster' (Maechler, 2019) and 'nbclust' (Charrad et al., 2014).

5.4.3.1.4 Implementing the Clustering Algorithms

Selection of a clustering algorithm takes place alongside these steps, and is informed by the kind of data available, the distance measure computed, and the type of analysis pursued. Two of the most common types of clustering algorithms are partitioning and hierarchical methods (Kaufman and Rousseeuw, 2009). Partitioning methods construct *k* clusters by classifying data into *k* groups, where *k* is given by the researcher and usually determined separately. The groups contain none of the same data points. Hierarchical clustering divides or agglomerates data into groups as small as one to as large as the entire data set (Kaufman and Rousseeuw, 2009). In the learning analytics literature, partitioning methods are far more dominant (Khalil and Ebner, 2017; Arora et al., 2017; Kovanović et al., 2016; Ferguson et al., 2015; Ferguson and Clow, 2015; Kizilcec et al., 2013), though hierarchical has been used (Chen et al., 2015), as well as other techniques that form clusters (Anderson et al., 2014; Ramesh et al., 2014). My analysis explores the more common approach of partitioning methods.

Within partitioning methods, two dominant approaches are k-means and k-medoids. Both methods work to minimise the within-cluster variation of objects, using two different approaches (Tibshirani, 2013). K-means is an algorithm that minimises the sum of the squared error between data objects in a cluster and the centroid of that cluster. It begins by selecting random centre points of clusters and proceeds iteratively. K-medoids works in a similar fashion; however, instead of selecting an arbitrary centre point for the cluster, it selects an actual data point from the data set, and proceeds to minimise the sum of the dissimilarities between it and the observations assigned to its cluster. Each of these methods proceeds iteratively until the intra-cluster variation is minimised (Kassambara, 2017).

A K-medoids-based approach was selected for my cluster explorations for two reasons. First, I wanted to be consistent across both cluster explorations in terms of the methods used. K-means works well with Manhattan Distances; however, it is not operable with the Gower Dissimilarity matrix. Second, it seemed sensible to base the clusters on central points representing actual observations in the data; in this case, an actual learner, as opposed to a mean point (Tibshirani, 2013). Therefore, algorithms based on partitioning around medoids were used, which can take either Manhattan Distance or Gower Distances. The primary k-medoids algorithm, PAM (Kaufman and Rousseeuw, 2009), is computationally expensive. Therefore, a more modern instantiation, CLARA, which leverages k-medoids-based clustering but does so on samples of the data set and is much faster, was used for the first cluster analysis with Manhattan Distances. CLARA, however, is not optimised for Gower Distance, so the traditional PAM algorithm was used for the second cluster analysis.

R packages utilised for these implementations included ‘cluster’ (Maechler, 2019) and ‘nbclust’ (Charrad et al., 2014).

5.4.3.2 Post-cluster Analysis

Once cluster analysis is conducted, the clusters are described, explored, and visualised. Tables and visualisations help illustrate the demographic distribution of education level and SES within clusters. These visualisations are paired with a univariate, multinomial logistic regression. Multinomial logistic regression models the log odds of nominal outcome variables, like the clusters, in relationship to the explanatory variables (Torres-Reyna, 2012; Long and Long, 1997). This is not an exercise in predictive modelling, however, and there is certainly no claim to causality. Indeed, the models only include one explanatory variable, education level or SES, and the Akaike Information Criterion (AIC) is quite high in absolute terms, though there is no comparison model to assess it relatively speaking. Instead, multinomial logistic regression is exploratory, and is utilised to make sense of the relative distributions of education levels across clusters. A similar analysis is conducted with SES, on clusters formed from percent grade, a participation and performance metric, and education level. This will contribute to the literature's present ambiguous answer regarding whether demographic background variables influence student engagement and outcomes in MOOCs (Joksimović et al., 2018; Gardner and Brooks, 2018), though it certainly does not resolve it.

5.4.4 Research Context and Ethics

5.4.4.1 Research Context

As discussed in **Section 3.3**, during my studies I was fortunate to maintain a formal academic visiting appointment with a major research university in the USA, which provided me with research facilities and support, access to data, and access to the MOOC producers interviewed in **Chapter 6**. While categorised as an R1, 'Very high research activity' university according to the Carnegie Classification (2017), the university also maintains a commitment to inclusive higher education, with a particular focus on broadening access and success to underrepresented populations. Toward that end, the university recently developed a series of nine entry-level MOOCs that could help earn a student admission into the university. The courses were a mix of humanities and STEM, and will be discussed further below. To adhere to a high level of privacy and duty of care for my research participants in **Chapter 6**, as well as sensitive partnerships, I choose to not disclose the institution. This helps maintain the strict confidentiality of my research participants, particularly the MOOC producers I interviewed in the subsequent chapter. This follows the guidance in sections 40 and 41 in the Ethical Guidelines for Educational Research from the BERA (BERA, 2018).

Several ethical considerations for this study were shaped by the Internal Review Board (IRB) process of the host university. Additionally, as described below, working with this host university was helpful, but also limiting in some operational and logistical respects.

5.4.4.2 Ethics

In **Section 3.4,** I describe the wide range of ethical considerations made during this research process. A few pertinent issues regarding my quantitative study are discussed below.

First, this study was approved by the research ethics processes of both the University of Cambridge and the host university in the USA. These approvals are appended to this thesis as **Appendix 3.1** and **Appendix 3.2**.

In this chapter, as in **Chapter 6**, I redact all information specifying the university that hosted me. This seeks to safeguard participants' anonymity. I also redact the names of corporate partners and technology providers, to not disclose sensitive information, as well as to further safeguard the participants' anonymity. The only noteworthy exception to this is edX, the MOOC platform. The scope of my project focuses primarily on xMOOCs and similar virtual learning experiences, and Coursera and edX are by far the largest providers of these kinds of courses in the USA. Universities frequently collaborate with both (Shah, 2020), as does my host university. As such, this detail does not risk disclosing any particularly identifiable information.

Issues of informed consent regarding data collection are tricky in digital education research (BERA, 2018). This is a particularly salient issue in the learning analytics community, for which the guidance and perspectives are evolving (Tsai and Gašević, 2017). My data were derived from edX, which has standardised legal disclaimers that provide for user data to be analysed for academic and commercial purposes, to which all learners must affirm consent.

This level of informed consent meets the minimal criteria set out by both the BERA (2018) and the British Psychological Society (Hewson and Buchanan, 2013). That said, the edX disclosure, while transparent in explaining the type of research likely to be conducted with user data, obviously cannot include exact details of all the potential studies for which this data will be used, including my own. Furthermore, users are supposed to be able to have access to a mechanism to not participate in a study should they choose. While this is possible, the process is cumbersome. At the same time, my study does not involve interventions or heterogenous treatments, which raise some of the thornier ethical issues in MOOC research (Kizilcec and Brooks, 2017), and educational social science more generally (Fives et al., 2015).

Overall, these issues are not settled adequately in the field. My study follows common procedures in learning analytics and digital education research and takes extra precautions to anonymise my affiliations to safeguard the identities of my research participants. I generally trust that the precautions and standards of the field, while perhaps inadequate, are for the time being sufficient.

The matter of data security is more straightforward. In accordance with the IRB approval of my host university, all data is stored on approved storage media, including Google Drive, Dropbox, and secure servers. These can only be accessed with formal credentials from the host institution. The data were not shared with anyone else who did not obtain separate authorisation.

5.4.5 Data

Data integration and 'wrangling' are an essential part of all data analytics work, particularly in helping translate analytic insights into actionable information to improve outcomes. Closing these gaps in an educational context can be particularly difficult, as many educational institutions face challenges in understanding what analytics are and how to utilise them properly (Ferguson et al., 2017; Clow, 2014). At the same time, analytics are promising, especially in educational contexts, insofar as they allow for diverse data on student characteristics, behaviours, and outcomes to be analysed alongside each other, offering the possibility for deeper analysis and insights (Chatti, Muslim, and Schroeder, 2017). To execute my quantitative analysis, considerable data wrangling was required. In what follows, the process of data integration is described, after which key variables of interest are specified.

Data for the analysis in this chapter is derived from the host university's sequence of nine MOOCs that collectively represent entry-level university credits for first-year students. These courses offer a mix of science- and math-focused content alongside humanities and social science content. Specific courses themselves were not utilised as units of analysis, which is a limitation of this research. Data were collected between the fall of 2017 and the spring of 2020.

Data from a variety of different sources were merged to build the final data set, including edX enrolment data, host university registrar data, before the course survey data, host university gradebook data, edX activity log data, and American Community Survey data from Opportunity Insights. These data integration processes are represented in **Figure 5.2.** Data integration, cleaning, and transformation was executed in R (Team R), utilising a variety of programming packages, including 'tidyverse' (Wikham, 2017) and 'data.table' (Dowle et al., 2019). While not the focus of this paper, the process of accessing, merging, and cleaning the data itself required substantial effort, with assistance from data engineers at the host university. These processes and the many decisions and actors they entail are an underexamined feature of the MOOC and learning analytic literature (Samuelsen et al., 2019), substantially influence how analysis proceeds, may contribute to hegemonic design bias, and could be further examined in future research.

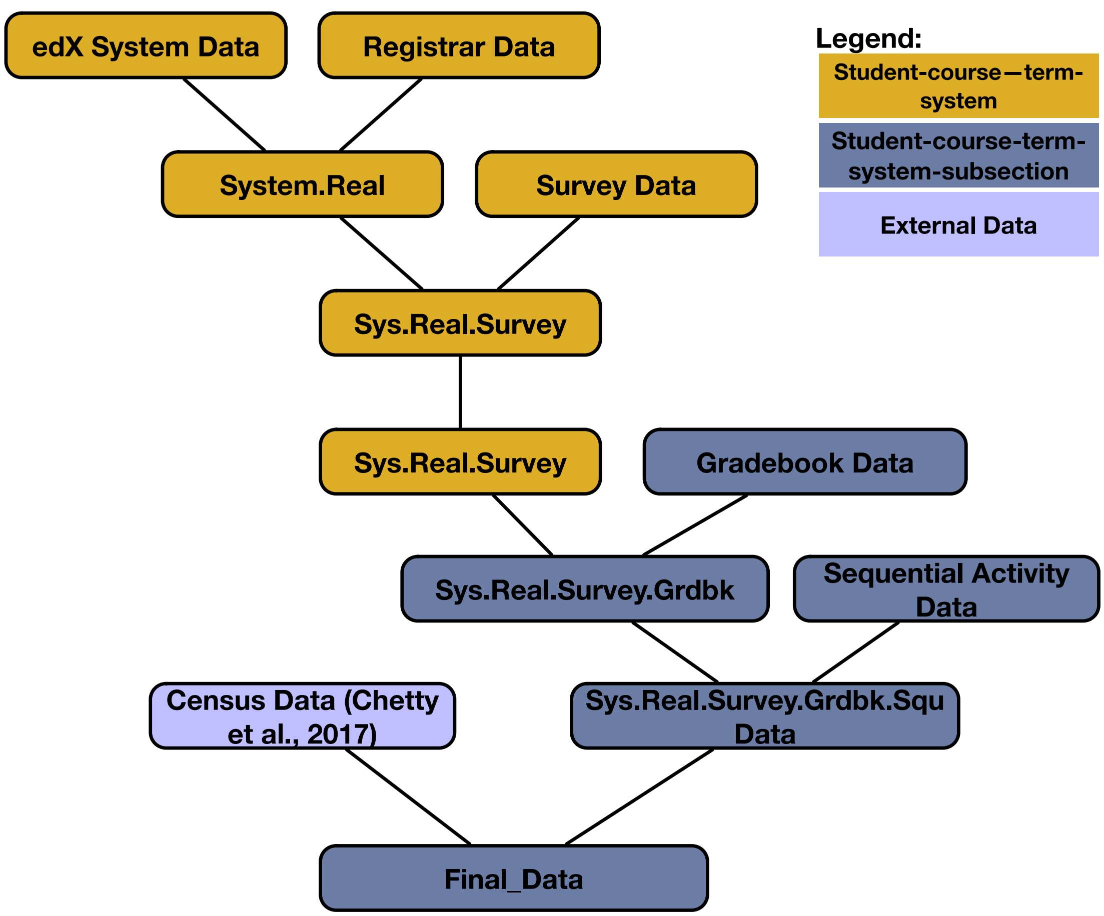


Figure 5.2: Data integration and wrangling processes.

Table 5.1 provides the enrolment data from the edX system on educational background level, gender, and geographic location for 260,239 learners who enrolled in the nine courses represented in the data, administered across 58 different course-terms. This represents the initial data set of users. The enrolment data reflects both common and unique features compared to the general MOOC literature. College-educated learners are overrepresented, comprising 56 percent of the enrolment, compared to 23 percent of students without a college degree. While college-educated learners are overrepresented, the proportion is lower than is common in the MOOC literature, where college-educated learners typically comprise between 60 to 80 percent of enrolments (Meaney and Fikes, 2018).

Additionally, 21 percent of students did not disclose their educational background. I chose to not drop these students, nor to use imputation methods to estimate educational background for this missing data. I included these students to conduct analysis on as large and reflective of the data set as possible, and because including the data as unknown did not detract from the analysis. Additionally, dropping incomplete cases biases data (Si and Reiter, 2013), and there is some evidence that students less likely to disclose demographic information may be more likely to come from underrepresented backgrounds (Jang and Vorderstrasse, 2019). I chose not to impute educational level data for several reasons. First, 21 percent is a substantial amount of data; while imputation methods have grown more sophisticated and can be quite accurate, they still carry with them the introduction of bias and error (Si and Reiter, 2013; Lodder, 2013). Second, including the data as unknown is itself akin to constant imputation of a random categorical variable level. Third, the analysis most at risk of including the Unknown variable level, the Gower-distance based clustering, is impacted in a predictable way. Namely, the Dice Coefficient component of Gower distance will separate clusters along binary dimensions of categorical variables. When Unknown is excluded from the analysis, four clusters are derived, two for each education background level, College Plus and No College; when unknown is included six clusters are derived, two for each education background level, College Plus, No College, and Unknown. This is further discussed in **Appendix 5.1**. While I believe these decisions are sensible, alternative approaches could have been pursued, and that a fifth of learners included in this study have no educational background data does represent a significant limitation.

Table 5.1: Descriptive statistics for enrolled learners in study sample. A total of 260,239 enrolled learners represented in the data for nine entry-level MOOCs, administered from 2017-2020 across 58 course-terms of students. N = 260,239.

Characteristic	**Overall**, N = 260239	**USA**, N = 49195[1]	**Outside USA**, N = 179155[1]	**Unknown**, N = 31889[1]
Education_Level				
College Plus	145399 (56%)	20299 (41%)	103721 (58%)	21379 (67%)
No College	59790 (23%)	15958 (32%)	37344 (21%)	6488 (20%)
Unknown	55050 (21%)	12938 (26%)	38090 (21%)	4022 (13%)
Gender				
Female	105585 (41%)	23273 (47%)	70121 (39%)	12191 (38%)
Male	108522 (42%)	14854 (30%)	77850 (43%)	15818 (50%)
Other	1676 (0.6%)	580 (1.2%)	1017 (0.6%)	79 (0.2%)
Unknown	44456 (17%)	10488 (21%)	30167 (17%)	3801 (12%)

[1] Statistics presented: n (%)

Table 5.2 presents the final data set of learners for which both gradebook and activity log data were present, which comprises the subset of 29,083 learners included in the cluster analyses. Limiting the analysis in this manner follows Wang et al. (2018), who defines the 'committed learner' as a student who submitted an assignment after the online analogue of 'add/drop period' of the course, representing a sample of 4.8 percent of total enrolled learners in their data set. In my sample, I broadened the 'committed learner' definition to include any learner who submitted a graded assignment during a course sequential. The 29,083 learners included in cluster analyses represented 11.2 percent of my total data set. Limiting the sample to 'committed learners' does carry some limitations, considered in conclusion. Highly subsetted data is common across the MOOC literature and remains an area for improvement (Gardner and Brooks, 2018). Notably, the overall proportion of tertiary-educated learners decreased from enrolment to the committed learner sample, while non-tertiary educated learners increased. That said, college-educated learners still account for 52 percent.

Table 5.2: Descriptive statistics for 'committed learners' included in cluster analyses. A total of 29,083 learners with gradebook and activity data represented in nine entry-level MOOCs offered by the host university from 2017-2020, accounting for 58 course-terms of students. N = 29083.

Characteristic	**Overall**, N = 29083	**USA**, N = 9708[1]	**Outside USA**, N = 15625[1]	**Unknown**, N = 3750[1]
Education_Level				
College Plus	15084 (52%)	3415 (35%)	9094 (58%)	2575 (69%)
No College	7951 (27%)	3778 (39%)	3463 (22%)	710 (19%)
Unknown	6048 (21%)	2515 (26%)	3068 (20%)	465 (12%)
Gender				
Female	13089 (45%)	4678 (48%)	6748 (43%)	1663 (44%)
Male	11093 (38%)	2952 (30%)	6436 (41%)	1705 (45%)
Other	241 (0.8%)	132 (1.4%)	97 (0.6%)	12 (0.3%)
Unknown	4660 (16%)	1946 (20%)	2344 (15%)	370 (9.9%)

[1] Statistics presented: n (%)

5.4.5.1 Key Variables of Interest

As described in the methods section, two sets of analyses are conducted in this exploratory study. The first is a cluster analysis based on computed Manhattan Distances between observations on two variables of interest: percent grade, and a participation and performance metric. These clusters are described and subsequently enriched by education level data and event count data. Similarly, the second cluster analysis utilises percent grade and a participation and performance metric, but also includes education level. This requires the utilisation of the Gower Distance metric, which can measure distances across mixed data types. These clusters are described, then enriched by approximated SES data and event count data. The participation and performance score, detailed further below, was devised in a similar way to the extant literature (Kizilcec et al., 2013).

The limited variables utilised in this study represents a shortcoming; the features I had at my disposal, and ultimately the features I selected, constrained the analytical process. Several social and technical considerations influenced this. The host university was extremely accommodating and generous in data access. At the same time, the host university was in the process of setting up their data architectures amidst my study, which made the data wrangling cumbersome and somewhat limited. It also imposed considerable time burdens on their already overextended staff. Concurrently, as the nature of my study evolved, I was constrained by my own limitations; what I originally planned and could do during the second year of my studies significantly dictated what I was able to do during my fourth year, despite my own skills and understanding evolving.

As a result, the variables included in my analysis consist of education level, percent grade, a computed participation and performance metric, total event counts, and, when applicable, approximated SES. The clusters, and the descriptions thereof, are limited to those variables. The nature of this proposed study, however, was to determine whether subgroups based on educational level and SES differed across observed clusters. For these specific questions, the variables at my disposal were sufficient, though the description of the behaviours is limited.

5.4.5.1.1 Education Level

Education level was obtained from the edX enrolment data. This data was used instead of survey data because it had a much higher completion rate. Users could select from nine potential levels, including: None, Junior High School, High School, Postsecondary Degree, Associate's Degree, Bachelor's Degree, Master's Degree, Professional Degrees, and Other. Variables were recoded into College Plus, No College, and Unknown. Postsecondary degrees, including Associate's, Bachelor's, Master's, and Professional Degrees, were grouped into College Plus, while None, Junior High School, and High School were grouped into No College. Other and non-responses were grouped into Unknown. Grouping Other into Unknown represents a limitation, as this could group learners with doctorates, which some studies have found represent between one to ten percent of learners (Ho et al., 2014), with learners with little to no education at all.

5.4.5.1.2 Percent Grade

Percent grade represented the learners' total grade in the course. This is primarily comprised of quizzes and tests.

5.4.5.1.3 Participation and Performance

Computing a participation and performance grade was motivated by the literature. Kizilcec et al. (2013) was one of the first papers to cluster MOOC data based on student behaviour, a method utilised by Ferguson and Clow (2015) and Ferguson et al. (2015), and others. Two typical clusters observed in the literature are 'solvers,' who complete quizzes and tests successfully but do not engage as much with the rest of the course, and 'all-rounders,' who successfully complete quizzes and tests while also engaging more throughout the course. Including a participation and performance metric can help differentiate between these two groups.

Kizilcec et al. (2013) analyse data from nearly 100,000 students participating in three courses offered on the Coursera platform. To do so, they first compute a description for each learner based on how that learner engaged throughout the course. They then apply clustering techniques to identify subpopulations based on these engagement descriptions. To accomplish the first computation for how a learner engaged throughout the course, they labelled participants during each assessment period as on-track (T; did the assessment on time), behind (B; completed the assessment late), auditing (A; watched videos and engaged materials but did not complete the assessment), or out (O; no course activity at all). Scores 0-3 were assigned to each participant (0 = O, 1 = A, 2 = B, 3 = T). Similarity scores were then computed for each participant using the Manhattan Distance method, and then the K-means clustering algorithm was applied.

Ferguson and Clow (2015) leveraged an augmented version of the Kizilcec et al. (2013) methodology on three FutureLearn courses. They reported that their initial replication of the methods utilised by Kizilcec et al. (2013) did not yield fruitful results; this is, in part, potentially attributable to the fact that Kizilcec et al. (2013) deployed their method on data from Coursera, while Ferguson and Clow (2015) deployed this methodology on data from FutureLearn. To provide a more granular accounting of learner behaviour and account for a wider range of actions, they coded student behaviour along an eleven-point framework, as opposed to a 0-3 framework like Kizilcec et al. (2013). Furthermore, they utilised Euclidian distance as their similarity metric.

I employ a similar method to Kizilcec et al. (2013) and Ferguson and Clow (2015) in computing the participation and performance score, with two important differences. I assign scores of 0-4, accounting for 0 = dropped from course, 1 = never-graded lurking, 2 = ever-graded lurking, 3 = graded and behind, and 4 = graded and on track. Second, I assign this grade for each graded course sequential, rather than assessment period, which ranges from course to course between 22 to 48 sequentials per course. This captures activities in between assessment periods, allowing for a more granular accounting of student participation and performance. To norm the score across the different course lengths, student total scores were summed and then divided by the number of total graded sequentials in the course.

5.4.5.1.4 Event Counts

Total event counts are not included as features during the cluster analysis. Event counts, however, are considered in describing the clusters. Event count is a generic, numeric variable representing the total number of actions a learner executed during a course. Activity-based features, like event counts, are commonly used in the literature as a measurement of engagement (Gardner and Brooks, 2018). Typically, this is approached with more sophistication, differentiating types of events, looking at events of specific time epochs, and other ways of enriching the data. A limitation of my study is that these were not pursued.

5.4.5.1.5 Socioeconomic Data

Survey data, while integrated into the final data set, was not utilised in the final analysis. The survey data did, however, provide a learner's longitude and latitude coordinates, which were paired with income level data at the Census tract level to derive approximated SES. Only students from the USA who completed the before the course survey were assigned SES, so it was a small subset compared to the entire sample. While SES status is an unfortunately rare variable included in MOOC data analysis, this approach has been utilised before (Ganelin and Chuang, 2019) as well as similar approaches (Hansen and Reich, 2015). SES data is leveraged in the second clustering analysis. SES was defined in relation to what is considered a 'low-wage' worker, a person making two-thirds or less the median national income (Escobari et al., 2019; Ross and Bateman, 2019). Census tracts in which the median household income was two-thirds or below the national median income in 2016, calculated to be $41,609.68, were labelled Low-SES, whereas all others were labelled Medium- to High-SES. There are several limitations with this approach that will be considered in conclusion; most notably, students who opt into MOOC surveys may likely be more engaged than that typical user (Kizilcec and Schneider, 2015). Second, approximating SES via Census tract, while a common approach, has significant shortcomings. Notably, each Census tract is comprised of between 3,000 and 5,000 people. Some heterogeneity within those tracts is likely, and it is entirely possible that higher-income individuals live within the boundaries of what may be considered a lower SES Census tract. Additionally, this type of analysis, while covered in privacy protocols users agree to in both taking the MOOC itself and in completing the additional survey, raises concerns about the threshold for what informed consent means.

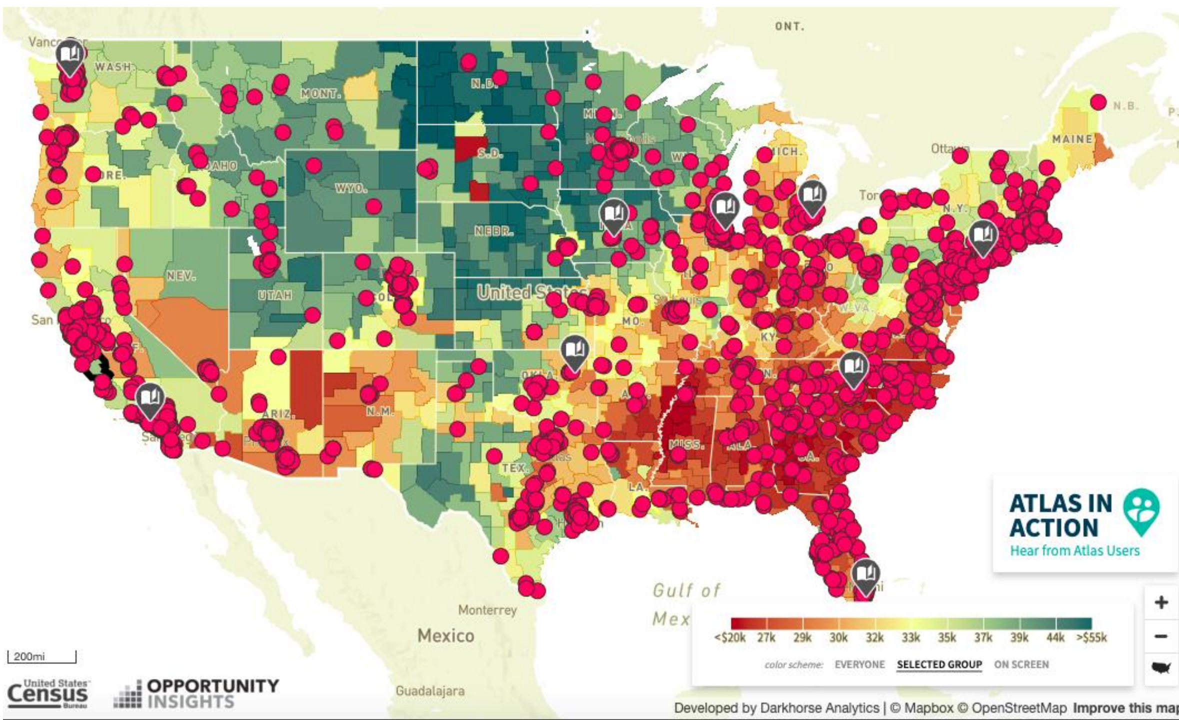


Figure 5.3: Approximated Socioeconomic Status (SES) of MOOC learners. Greener areas represent higher socioeconomic geographies; redder areas represent lower socioeconomic geographies. Census data compiled by Opportunity Insights at Harvard.

5.5 Analysis and Results

The following analysis and results sections present the outcome of the two cluster analysis investigations described in the methods section, **Section 5.4.3**.

5.5.1 Analysis and Results: Manhattan Distance, CLARA-based Clusters

In the first cluster analysis, learners are clustered based on Manhattan Distances (Kravvaris et al., 2016; Loohach and Garg, 2012) and the CLARA algorithm (Schubert and Rousseeuw, 2019). The features of interest utilised to produce the clusters were percent grade, and a composite participation and performance metric. After clustering, the relative distributions of education level across clusters are considered, which is then evaluated using multinomial logistic regression.

5.5.1.1 Determining Clusterability

After features are selected for evaluation and Manhattan Distances between the observations across the features are computed, clustering tendency is assessed (Kassambara, 2017). In addition to taking indication from the literature (Li and Baker, 2018), a Visual Assessment of Clustering Tendency (VAT) is produced, which presents an ordered dissimilarity matrix (Kassambara, 2017). **Figure 5.4** below shows the visualisation of the ordered dissimilarity matrix for the MOOC data at left, and on the right the VAT for a random set of 10,000 data points. Assessment of the VAT is somewhat ambiguous, as there are no dark-coloured squares along the diagonal, an indication of distinct clusters. The pattern, however, is clearly non-random. Based on the existing literature, as well as the VAT, we can infer some grouping structure to the data. This can be further assessed when determining the appropriate number of clusters to explore (Kassambara, 2017).

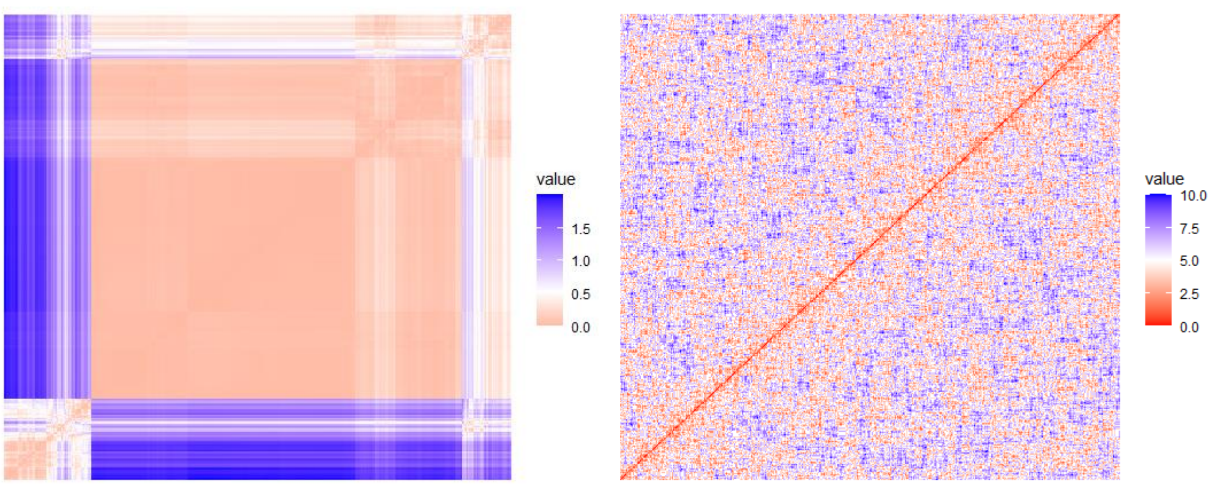


Figure 5.4: Visual Assessment of Clustering Tendency (VAT) of MOOC learner data versus random data, based on Manhattan Distances. The figure at left demonstrates the VAT for the MOOC learners data based on Manhattan Distance measures. The figure at right shows the VAT for a Manhattan Distance matrix of 10,000 randomly generated data points, which does not form natural clusters. Red indicates high similarity, and purple indicates low similarity.

5.5.1.2 Determining Number of Clusters

To determine the appropriate number of clusters to explore, average silhouette widths are computed. Similar to Ferguson and Clow (2015), silhouette width analysis was not particularly useful. **Figure 5.5** shows the average silhouette widths observed when partitioning the data into a minimum of two groups and to a maximum of ten. The silhouette width is greatest for two clusters, which may not be particularly meaningful, given that, typically, four subgroups of learners are often observed. A mild inflexion point, which may indicate a salient number of clusters, can be seen at four clusters, and a sharper one at nine, though the silhouette width at nine clusters is below .5, indicating somewhat weak clustering. This is an ambiguous result. Therefore, another method for determining the best number of clusters was implemented, the gap statistic method (Tibshirani et al., 2001).

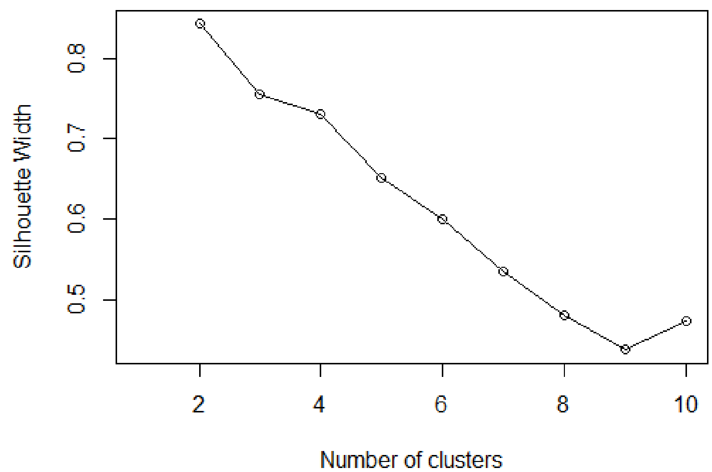


Figure 5.5: Silhouette plot of the CLARA clustering algorithm for k=2:10.

Figure 5.6 shows the output of implementing the gap statistic method with 100 Monte Carlo Bootstrapped random samples as the null reference set against a CLARA implementation of 30 samples of 1,000 data points from the MOOC data. The ideal number of clusters is determined to be three, with another levelling off of the gap statistic occurring at five; levelling can serve as an informal heuristic for potential investigation (Stack Exchange, 2014). While a very rigorous approach, the result of three clusters differed slightly from the four to five clusters commonly found in the literature (Li and Baker, 2018).

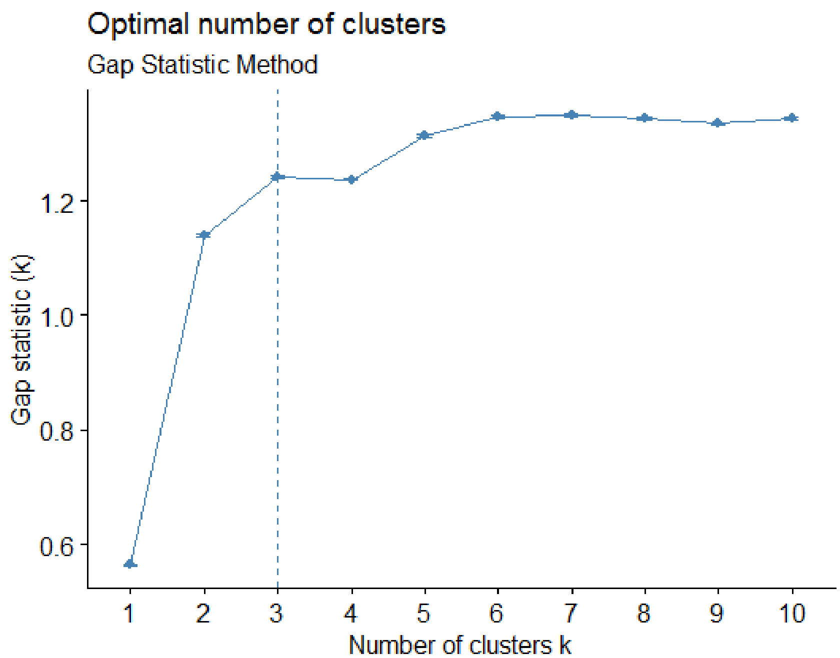


Figure 5.6: Estimates of the ideal number of CLARA-based clusters utilising the gap statistic method.

5.5.1.3 Cluster Analysis and Descriptions

Given the ambiguity in the results, clusters three through five were explored. Four clusters yielded a result similar to clusters found in the literature of disengagers, auditors, solvers, and all-rounders (Li and Baker, 2018). Five clusters broke the disengagers into two groups with different engagement profiles. As a result, five clusters were selected for further analysis. **Table 5.3** presents descriptive statistics of the five clusters. Leveraging common nomenclature from the literature (Li and Baker, 2018), the clusters are divided into the following categories: All-rounders, Auditors, Disengagers, Samplers, and Solvers. **Figure 5.7** provides a visualisation of the clusters along the percent grade axis and the participation and performance metric axis.

- **All-rounders** accounted for 9.6 percent of the total sample. These learners achieved high marks in their courses, as reflected in their percent grade median of 89 percent, with an interquartile range of 81 percent to 94 percent. They actively engaged throughout the course, obtaining a participation and performance metric median score of 94 percent, with an interquartile range of 88 percent to 96 percent. They similarly had the highest median total event count of 4,586. The computed ratio of percent grade to participation and performance metric, called relative grade to engagement ratio, was .96, indicating consistent engagement. This is further contextualised below when compared to the Solver.

- **Auditors** accounted for 7.1 percent of the total sample. These learners engaged with the course, obtaining a participation and performance median grade of 45 percent, with a median event count of 2,940. They scored less in their overall percent grade, with a median of 33 percent. This group did, however, have the largest range of interquartile median for both participation and performance and percent grade.
- **Disengagers** accounted for 61 percent of the total sample. The largest group, these learners demonstrated little engagement and performance in the course, with a median percent grade of 0, and a participation and performance metric median of 2 percent.
- **Samplers** accounted for 17 percent of the total sample. These learners dropped off early in the course, though they did register some engagement and achievement, with a median participation and performance grade of 16 percent, and a total percent grade of just 5 percent at the median. The event count median was 1,087, considerably higher than the disengaging group, which dropped off with far fewer events and had considerably less engagement and less achievement.
- **Solvers** accounted for 4.9 percent of the total sample. These learners achieved high marks in their courses, though they did so while engaging considerably less. This is observed by their high percent grade median of 88 percent, and their relatively low participation and performance metric median of 46 percent. Their relative grade to engagement ratio was very high at 1.84, nearly double that of the All-rounders, meaning that these learners achieved roughly the same score while engaging with far fewer course sequentials, and likely in a more strategic, optimised way. They also had a lower event count median of 4,145.

Table 5.3: Descriptive statistics for the five clusters of learners determined by the CLARA algorithm: All-rounders (9.6 percent), Auditors (7.1 percent), Disengagers (61 percent), Samplers (17 percent), and Solvers (4.9 percent). N = 29,083.

Characteristic	**Overall**, N = 29083	**All-rounders**, N = 2799[1]	**Auditors**, N = 2075[1]	**Disengagers**, N = 17817[1]	**Samplers**, N = 4971[1]	**Solvers**, N = 1421[1]
Education_Level						
College Plus	15084 (52%)	1514 (54%)	1012 (49%)	9452 (53%)	2550 (51%)	556 (39%)
No College	7951 (27%)	792 (28%)	692 (33%)	4379 (25%)	1505 (30%)	583 (41%)
Unknown	6048 (21%)	493 (18%)	371 (18%)	3986 (22%)	916 (18%)	282 (20%)
Part_and_Perf	0.05 (0.02, 0.23)	0.94 (0.88, 0.96)	0.45 (0.36, 0.59)	0.02 (0.02, 0.04)	0.16 (0.12, 0.22)	0.46 (0.38, 0.56)
Percent_Grade	0.01 (0.00, 0.11)	0.89 (0.81, 0.94)	0.33 (0.22, 0.44)	0.00 (0.00, 0.01)	0.05 (0.03, 0.09)	0.88 (0.79, 0.93)
Event_Count_total	547 (202, 1850)	4586 (3176, 6676)	2940 (1856, 4433)	261 (129, 534)	1087 (620, 1825)	4145 (3070, 5634)
Relative_Grade_to_Engagement_Ratio	0.12 (0.00, 0.61)	0.96 (0.89, 1.00)	0.68 (0.47, 0.91)	0.00 (0.00, 0.10)	0.37 (0.20, 0.51)	1.84 (1.58, 2.31)

[1] Statistics presented: n (%); median (IQR)

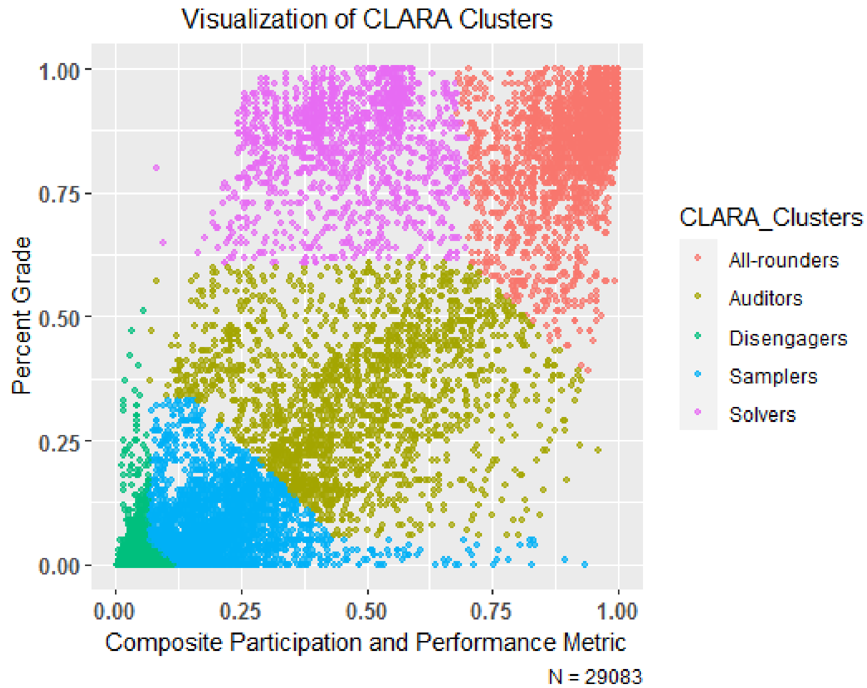


Figure 5.7: A representation of the five clusters determined by the CLARA algorithm. These include the commonly observed clusters in the literature: All-rounders, Auditors, Disengagers, Samplers, and Solvers. N = 29,083.

5.5.1.4 Educational Backgrounds of Learners across Clusters

When considering the educational background of the learners and how these subgroups dispersed across the clusters, more interesting insights emerged. These will be considered further in the discussion. **Table 5.4** presents the absolute and relative values of the different educational background levels distributed across the clusters. **Figure 5.8** presents this visually.

Table 5.4: Distribution of education level across the five clusters determined by the CLARA algorithm. N = 29,083.

Characteristic	**Overall**, N = 29083	**College Plus**, N = 15084[1]	**No College**, N = 7951[1]	**Unknown**, N = 6048[1]
CLARA_Clusters				
All-rounders	2799 (9.6%)	1514 (10%)	792 (10.0%)	493 (8.2%)
Auditors	2075 (7.1%)	1012 (6.7%)	692 (8.7%)	371 (6.1%)
Disengagers	17817 (61%)	9452 (63%)	4379 (55%)	3986 (66%)
Samplers	4971 (17%)	2550 (17%)	1505 (19%)	916 (15%)
Solvers	1421 (4.9%)	556 (3.7%)	583 (7.3%)	282 (4.7%)

[1] Statistics presented: n (%)

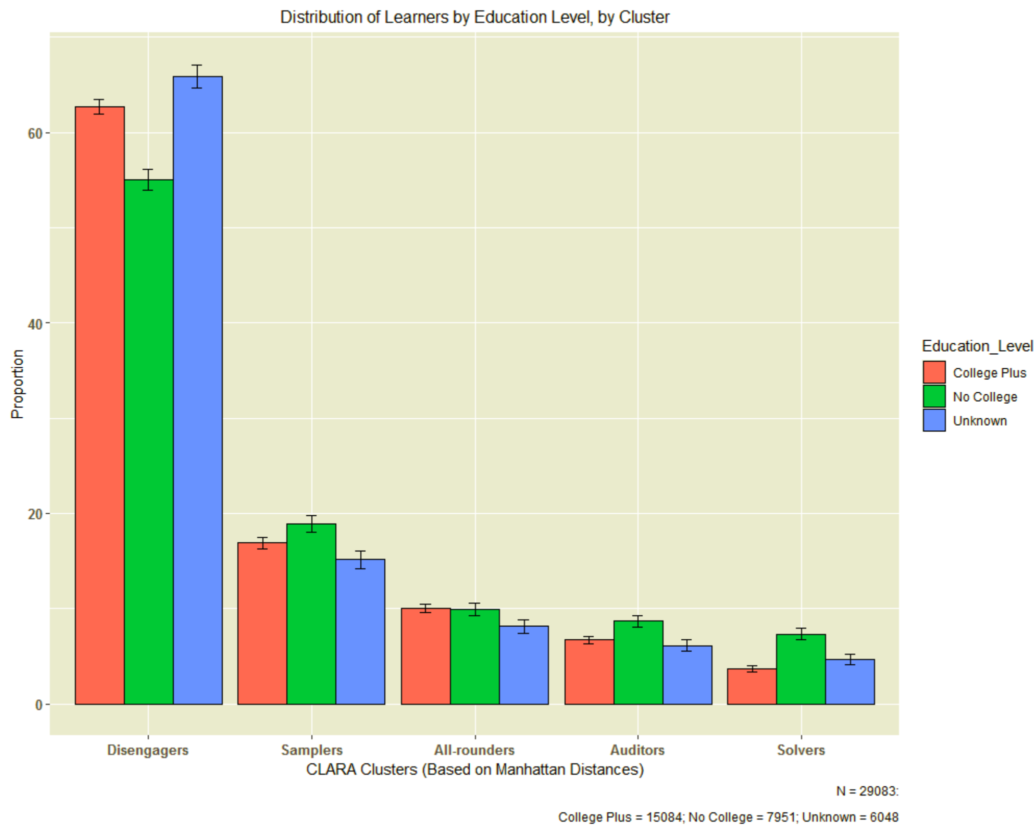


Figure 5.8: Distribution of educational background for students across five clusters determined by the CLARA algorithm. N = 29,083.

Table 5.5 presents the relative risk ratios, displayed as the exponentiated value of the logit coefficients from a multinomial logistic regression (Torres-Reyna, 2012), where educational level is the explanatory variable, and cluster the outcome variable. The reference category is College Plus learners in the Disengagers cluster. The coefficients described are statistically significant at the .01 level. No College learners are 2.263 times as likely to be solvers, and 1.129 times as likely to be All-rounders, compared to their College Plus, Disengaged counterparts. At the same time, they are 1.476 times as likely to be Auditors and 1.274 times as likely to be Samplers, compared to their College Plus, Disengaged counterparts.

Table 5.5: Relative Risk Ratios: Education Level and Cluster. Relative Risk Ratios, displayed as the exponentiated value of the logit coefficients from the multinomial logistic regression, where educational level is the explanatory variable, and cluster the outcome variable. College Plus, Disengagers are the reference group. N = 29,083

	Dependent variable:			
	All-rounders (1)	Auditors (2)	Samplers (3)	Solvers (4)
Education_LevelNo College	1.129^{**}	1.476^{***}	1.274^{***}	2.263^{***}
	(0.048)	(0.053)	(0.037)	(0.062)
Education_LevelUnknown	0.772^{***}	0.869^{**}	0.852^{***}	1.203^{**}
	(0.055)	(0.064)	(0.043)	(0.076)
Constant	0.160^{***}	0.107^{***}	0.270^{***}	0.059^{***}
	(0.028)	(0.033)	(0.022)	(0.044)
Akaike Inf. Crit.	67,391.750	67,391.750	67,391.750	67,391.750
Note:				*p<0.1; **p<0.05; ***p<0.01

5.5.2 Analysis and Results: Gower Distance, PAM-based Clusters

In the second cluster analysis, learners are clustered by the PAM algorithm based on Gower Distances. The purpose of this investigation is twofold. First, it seeks to determine whether utilising a categorical variable like education level is useful in the process of clustering. Second, it provides the opportunity to consider SES across clusters already controlling for education level, percent grade, and participation and performance. Additionally, few papers on MOOCs have leveraged Gower Distance measures, so the opportunity to implement it and possibly contribute a simple but meaningful mixed-type clustering use-case drove me to include these results.

Similar steps are followed as the previous investigation. First, cluster tendency is evaluated, and then the ideal number of clusters is determined. Once the data is clustered, descriptive features of the clusters are presented. Then, SES is considered, for which only a small proportion of user data is available from the USA. SES is analysed and presented in relation to the entire 'committed learner' data set of 29083 learners, despite only having SES data for 2342 learners. When limiting the Gower Distance-based cluster analysis to USA data only, six clusters are found, extremely similar to the six clusters found across the full sample of 'committed learners'; thus, there was no need to differentiate the clustering results further. This is considered further in **Appendix 5.1.** That said, that such a limited amount of SES data is available is a limitation of the study.

5.5.2.1 Determining Clusterability

The initial impetus of this investigation was informed by the literature; specifically, common clusters of students are regularly identified in MOOC data (Li and Baker, 2018). In addition to the literature, the VAT technique was utilised, which produced an ordered dissimilarity matrix based on Gower Distances. **Figure 5.9** below shows the visualisation of the ordered dissimilarity matrix for the MOOC data at left, and on the right the VAT for a random set of 10,000 data points, both based on computed Gower Distances. Again, the assessment of the VAT is somewhat ambiguous, as there are no dark coloured squares along the diagonal. At the same time, however, the dissimilarity pattern is clearly non-random. While a somewhat ambiguous result, proceeding to the next step, which involves determining the appropriate number of clusters, can provide further insight into whether the data can be clustered.

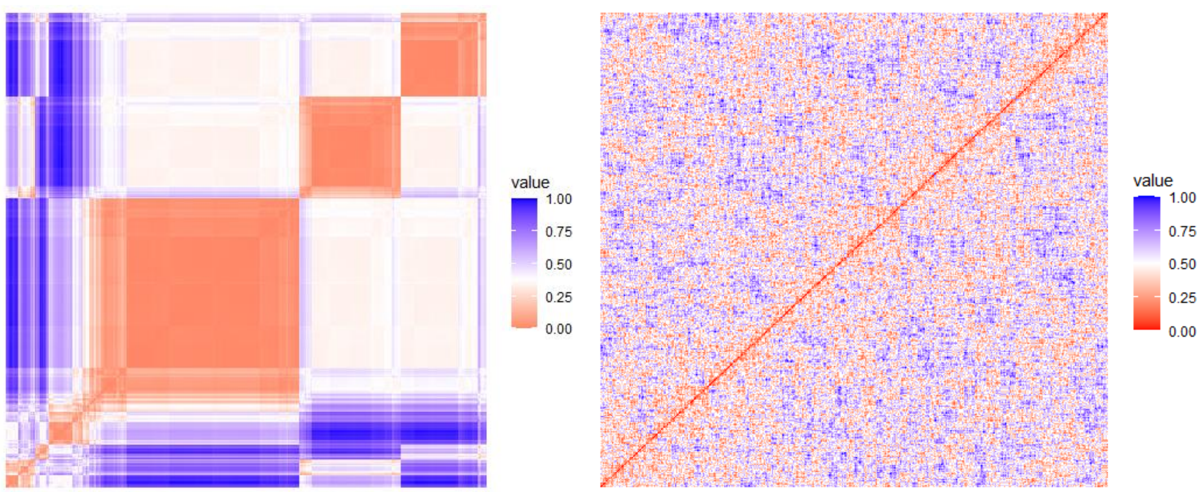


Figure 5.9: Visual Assessment of Clustering Tendency (VAT) of MOOC learner data versus random data, based on Gower Distances. The VAT at right shows 10,000 random data points of a Gower Dissimilarity matrix.

5.5.2.2 Determining Number of Clusters

As opposed to the first cluster analysis in this chapter, and in contrast to results in Ferguson and Clow (2015), silhouette analysis returned a highly interpretable and useful result. **Figure 5.10** indicates a clear high point occurring at six clusters with an average silhouette width of above .8, indicating well-clustered observations. Based on this finding, the PAM clustering algorithm will be implemented and specified to generate six clusters.

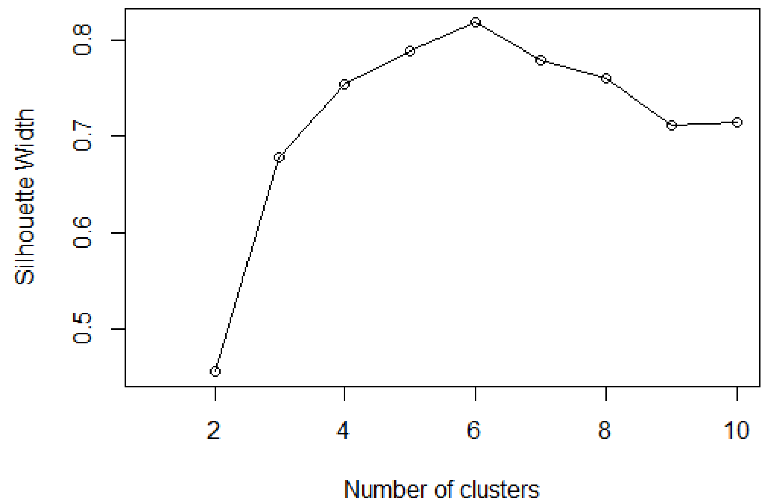


Figure 5.10: Silhouette plot of the PAM clustering algorithm for k=2:10. At six clusters, the average silhouette width for the data objects is above .8, indicating sound clusters.

5.5.2.3 Cluster Analysis and Descriptions

Partitioning the data into six clusters yields results that are somewhat interesting yet not surprising. Essentially, the algorithm splits the data into successful and unsuccessful students across educational backgrounds. This can, however, provide insight into how different educational groups are performing in comparison to each other, even when both are successful or not successful. Additionally, the common cluster types observed in the MOOC literature are not as evident in these clusters. While patterns similar to All-rounders and Disengagers are present across each education level, the Sampling, Auditing, and Solving cluster patterns are not observed. For these reasons, clusters will be labelled in the following manner: College Plus, All-rounders; College Plus, Disengagers; No College, All-rounders; No College, Disengagers; and Unknown, All-rounders as well as Unknown, Disengagers. **Table 5.6** presents descriptive statistics for the six clusters.

- **College Plus, All-rounders** accounted for 8.3 percent of the total sample. This cluster is composed of students with a tertiary degree who successfully completed their courses with a high degree of participation across course sequentials. They had a median percent grade of 87 percent, and a median participation and performance metric of 87 percent.

- **College Plus, Disengagers** accounted for 44 percent of the total sample, the largest group among all the clusters. These learners had a median percent grade of zero, a median participation and performance metric of 4 percent, and average event counts of 381. This group appears very similar to the Disengagers from the first set of clusters.
- **No College, All-rounders** accounted for 5.9 percent of the sample. They behaved similarly to College Plus All-rounders, with a median percent grade of 84 percent, and a median participation and performance metric of 71 percent. While still successful in their courses, these learners had lower overall percent grades and participation and performance metrics than the College Plus All-rounders. At the same time, they had a greater median event count than the College Plus All-rounders.
- **No College, Disengagers** accounted for 21 percent of the total sample. Like the College Plus Disengagers, these learners obtained a median percent grade of zero and a median participation and performance metric of 4 percent. They averaged 451 events, and fit patterns similar to the Disengagers from the first cluster analysis.
- **Unknown, All-rounders** accounted for 3.2 percent of the sample. This group obtained a median percent grade of 84 percent, a median participation and performance metric of 78 percent, and a median event count of 4,444. These numbers place learners in this cluster in between the College Plus and No College All-rounders. At the median, these learners achieved and participated slightly less than the College Plus All-rounder cohort, and slightly more than the No College All-rounder cohort.
- **Unknown, Disengagers** accounted for 18 percent of the sample. With very similar patterns to the first two groups of Disengagers from this cluster analysis, and similar to the Disengagers from the first cluster analysis, these learners obtained a median percent grade of zero, a median participation and performance metric of 3 percent, and 366 events at the median.

Table 5.6: Descriptive statistics of the six clusters determined by the PAM algorithm: College Plus All-rounders (8.3 percent), College Plus Disengagers (44 percent), No College All-rounders (5.9 percent), No College Disengagers (21 percent), Unknown All-rounders (3.2 percent), and Unknown Disengagers (18 percent). Total N = 29,083.

Characteristic	**Overall**, N = 29083	**College Plus, All-rounders**, N = 2411[1]	**College Plus, Disengagers**, N = 12673[1]	**No College, All-rounders**, N = 1710[1]	**No College, Disengagers**, N = 6241[1]	**Unknown, All-rounders**, N = 942[1]	**Unknown, Disengagers**, N = 5106[1]
Education_Level							
College Plus	15084 (52%)	2411 (100%)	12673 (100%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)
No College	7951 (27%)	0 (0%)	0 (0%)	1710 (100%)	6241 (100%)	0 (0%)	0 (0%)
Unknown	6048 (21%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)	942 (100%)	5106 (100%)
Part_and_Perf	0.05 (0.02, 0.23)	0.87 (0.60, 0.95)	0.04 (0.02, 0.09)	0.71 (0.52, 0.94)	0.04 (0.02, 0.11)	0.78 (0.54, 0.92)	0.03 (0.02, 0.08)
Percent_Grade	0.01 (0.00, 0.11)	0.87 (0.74, 0.93)	0.00 (0.00, 0.03)	0.84 (0.64, 0.92)	0.00 (0.00, 0.04)	0.85 (0.66, 0.92)	0.00 (0.00, 0.01)
Event_Count_total	547 (202, 1850)	4122 (2864, 6084)	381 (171, 881)	4384 (3133, 6191)	455 (179, 1084)	4444 (3162, 6224)	366 (141, 849)
Relative_Grade_to_Engagement_Ratio	0.12 (0.00, 0.61)	0.98 (0.89, 1.13)	0.00 (0.00, 0.35)	0.99 (0.86, 1.61)	0.00 (0.00, 0.38)	0.99 (0.86, 1.48)	0.00 (0.00, 0.23)

[1] Statistics presented: n (%); median (IQR)

5.5.2.4 Socioeconomic Backgrounds of Learners across Clusters

While data for only a small sample of survey completers was used to approximate SES status, enriching the clusters with this data provides deeper insight than just considering education level itself. It allows us to examine the SES distribution across the clusters, controlling for educational status, percent grade, and the participation and performance metric. **Table 5.7** presents the distribution of SES status across the clusters, where that data is available. Similarly, **Figure 5.11** provides a visualisation of the distribution of SES across clusters. Parameter estimates for Mid-High- and Low-SES have considerably wider confidence intervals resultant from the relatively small sample size. As discussed in **Appendix 5.1**, limiting the initial Gower Distance-based cluster analysis to USA-only data yielded extremely similar results to the Gower Distance-based cluster analysis on the full data set; therefore, SES is presented in relationship to the full data set. That such a limited amount of USA-only SES data is available is a limitation of the study.

Table 5.7: Distribution of Socioeconomic Status (SES) among learners across the six clusters determined by the PAM algorithm. Total N = 29,083.

Characteristic	**Overall**, N = 29083	**Unknown SES**, N = 26741[1]	**Low SES**, N = 458[1]	**Mid-High SES**, N = 1884[1]
PAM_Clusters				
College Plus, All-rounders	2411 (8.3%)	2284 (8.5%)	21 (4.6%)	106 (5.6%)
College Plus, Disengagers	12673 (44%)	12188 (46%)	74 (16%)	411 (22%)
No College, All-rounders	1710 (5.9%)	1364 (5.1%)	69 (15%)	277 (15%)
No College, Disengagers	6241 (21%)	5640 (21%)	120 (26%)	481 (26%)
Unknown, All-rounders	942 (3.2%)	685 (2.6%)	58 (13%)	199 (11%)
Unknown, Disengagers	5106 (18%)	4580 (17%)	116 (25%)	410 (22%)

[1] Statistics presented: n (%)

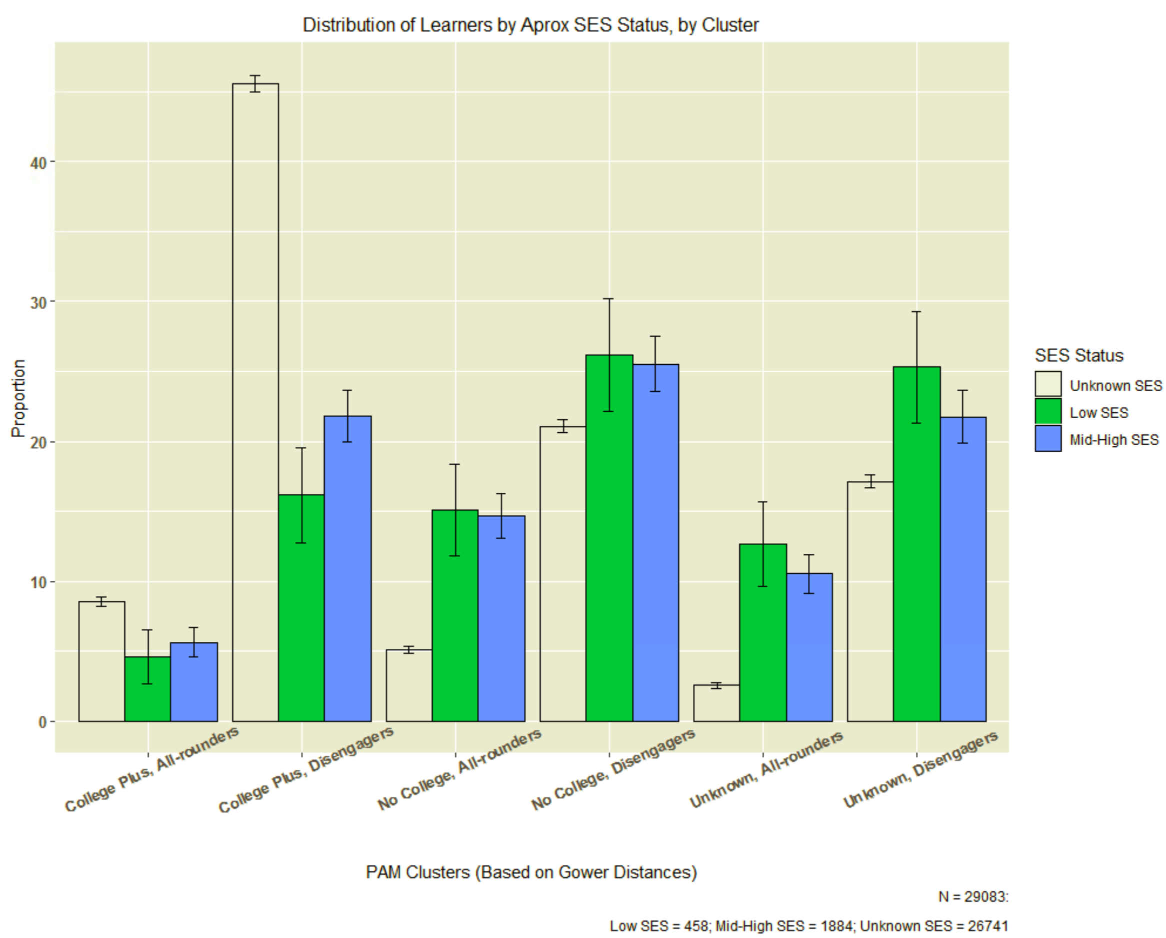


Figure 5.11: The distribution of known Socioeconomic Status (SES) across clusters determined in part by educational level. Total N = 29,083.

Table 5.8 presents the relative risk ratios, shown as the exponentiated value of the logit coefficients from the multinomial logistic regression (Torres-Reyna, 2012), where SES is the explanatory variable, and cluster is the outcome variable. The reference category is College Plus, All-rounders **from** Mid-High-SES backgrounds. Low-SES learners appear to be just as likely as their Mid-High-SES counterparts to be in any of the clusters, as none of the relative risk ratios registers statistical significance. This could be a sample size limitation. When looking at the coefficients, however, it appears at least possible that while a larger sample could validate Low-SES learners as more likely to be in the No College or Unknown education level clusters, they appear to be more or less evenly distributed across both the successful All-rounder group and the unsuccessful Disengaging groups.

Table 5.8: Relative Risk Ratios: Socioeconomic Status (SES) and Cluster. The relative risk ratios, shown as the exponentiated value of the logit coefficients from the multinomial logistic regression, where SES is the explanatory variable, and cluster is the outcome variable. College Plus, All-rounders from Mid-High SES backgrounds are the reference group. N = 29083.

	Dependent variable:				
	College Plus, Disengagers	No College, All-rounders	No College, Disengagers	Unknown, All-rounders	Unknown, Disengagers
	(1)	(2)	(3)	(4)	(5)
bi_SES_status_finalUnknown SES	1.376***	0.229***	0.544***	0.160***	0.518***
	(0.111)	(0.119)	(0.110)	(0.128)	(0.112)
bi_SES_status_finalLow SES	0.909	1.257	1.259	1.471	1.428
	(0.270)	(0.274)	(0.260)	(0.282)	(0.261)
Constant	3.878***	2.613***	4.538***	1.877***	3.868***
	(0.109)	(0.114)	(0.107)	(0.120)	(0.109)
Akaike Inf. Crit.	85,200.670	85,200.670	85,200.670	85,200.670	85,200.670
Note:					*p<0.1; **p<0.05; ***p<0.01

5.6 Discussion

Several prominent papers in the MOOC literature use learning analytic techniques like cluster analysis to discover clusters of learners (Li and Baker, 2018; Ferguson et al., 2015; Kizilcec, 2013). Whether it is worthwhile to include demographic variables like education level in these kinds of analyses is less clear (Joksimović et al., 2018). Some researchers find no relationship (Zhang et al., 2019; Brooks et al., 2015), and others finding lower-educated users struggling more (Engle et al., 2015), or, similarly, more educated users doing better (Kizilcec and Halawa, 2015). Analysis from this chapter suggests that education level does have some relationship with the likelihood of learners ending up in a particular cluster. Furthermore, analysis from this chapter also indicates that SES has no observable relationship to the cluster in which learners end up. These findings are limited to the learners taking the particular set of entry-level MOOCs examined. The discussion of these results will follow in the pattern of the analysis, first examining noteworthy findings from the Manhattan Distance and the CLARA algorithm exercise, and then from the second exercise of utilising Gower Distance and the PAM algorithm.

Before doing so, one broad, descriptive point is worth making that is pertinent to the MOOC movement and to hegemonic design bias from **Chapter 4**. At the top of the entry funnel for the set of nine entry-level MOOCs analysed in this chapter, tertiary-educated learners represented 56 percent of the more than 260,000 enrolments. Sub-setting this data to roughly 29,000 'committed learners' who submitted at least one assignment, tertiary-educated learners accounted for 52 percent of enrolments. These numbers reflect far broader inclusivity than the typical MOOC course in the existing literature, where between 60 and 80 percent of enrolled learners already have a college degree. Nonetheless, the prospect of whether MOOCs will ever serve as a democratising force in education should contend with these realities; that even for entry-level tertiary courses that can count toward university credit and admission offered by an institution committed to widening participation for traditionally underrepresented groups, already-educated learners still make up most enrolees.

At the same time, the analysis in this chapter presents provisional insights that, while the overall enrolment question may still be vexing, traditionally underrepresented learners can and do enrol in MOOCs and similar offerings, and they can and do persist. The first cluster analysis constructed clusters based on percent grade and a computed participation and performance metric and examined these clusters with regard to learner-indicated prior educational attainment. Multinominal logistic regression modelling exploring the relationship between education level and cluster assignment indicated that non-tertiary-educated learners were more likely to be Solvers, learners who attained high achievement in the courses with relatively lower engagement, as well as All-rounders, learners who achieved highly and engaged throughout the course compared to their higher educated, disengaging peers. Simultaneously, non-tertiary-educated learners were also more likely to be samplers, who engaged early in the course and then stopped out, or auditors, who engaged during the course but did not necessarily submit assignments for a grade. This could indicate that these learners need earlier support mechanisms to help translate initial or consistent engagement into scholastic achievement in the course.

The second cluster analysis pursued inquiries into whether demographic variables had a relationship to performance and achievement in the MOOCs by constructing clusters based on percent grade, computed participation and performance, and education level. These clusters were sorted into successful and unsuccessful learners across the education levels present, College Plus, No College, and Unknown, for a total of six clusters. When these clusters were enriched with approximated SES status data for a small subset of learners in the USA, multinomial logistic regression indicated that Low-SES learners were no more or less likely than their Mid-High-SES peers to sort into any of the other clusters. These insights are asserted with caution, as sample size issues limited the breadth of analysis capable along the SES dimension.

Regarding the existing literature, these results have several implications. First, while there is no consensus regarding the relationship between demographic variables like education level and MOOC engagement, some literature does indicate that traditionally underrepresented learners can be just as successful as their better represented, higher educated peers, especially in classes more intentionally designed for their demographic (Lambert, 2020; Wang et al., 2018; Goldberg et al., 2015). The results in this chapter offer provisional support for these conclusions and offer some evidence that observed patterns of better-educated learners performing better in MOOCs (Kizilcec and Halawa, 2015; Engle et al., 2015) need not necessarily be considered a forgone conclusion. Similarly, while the analysis of SES data was limited by sample size, the observed evidence of learners from high-SES backgrounds performing better in MOOCs (Ganeline and Chuang, 2019; Hansen and Reich, 2015) need not necessarily be assumed either. More research is needed to determine what specifically enabled these outcomes. Importantly, however, these outcomes suggest that the potential MOOC 'pivot' to focus on providing continuing education to already well-educated professionals may be premature (Reich and Ruipérez-Valiente, 2019). Additionally, results in this chapter suggest that taking a more explicit approach to investigating and analysing MOOC data across demographic variables would be a worthwhile and potentially promising way to move MOOCs back toward their original mission.

Beyond these outcomes, the analysis presented in this chapter also offers some methodological insights. Utilising a medoids-based clustering algorithm revealed the same kinds of clusters as the means-based approaches in extant literature (Li and Baker, 2018). Similarly, the approach to computing a participation and performance metric at the sequential level of the courses, as opposed to the assessment period, provided little additional insight into the clusters formed. Implementing the Gower Distance metric (Ebbert and Dutke, 2020; Gower, 1971) to more sensitively cluster subgroups with demographic variables, however, did achieve somewhat novel results. Specifically, utilising mixed-variable features to cluster data may reveal subgroups of underrepresented learners potentially more amenable to support and remediation interventions; for example, the group of No College, Disengaged learners observed in the second cluster analysis presented in this chapter.

5.7 Conclusion

This chapter aimed to analyse the following questions, derived from the existing literature consensus that clusters of learner groups are commonly observed in MOOC data (Li and Baker, 2018), but with little existing insight into whether those subgroups are differentiated by demographic variables like education background and SES:

- **RQ2: How are traditionally underrepresented students engaging with MOOCs?**
    - **RQ2.1**: **Do learners in entry-level tertiary MOOCs demonstrate similar patterns of clustering found in the broader MOOC literature?**
    - **RQ2.2: Are demographic subgroups of learners, specifically along the educational background dimension, represented equally across clusters?**
    - **RQ2.3: What demographic and engagement insights can be unveiled through leveraging a more novel, demographically-sensitive cluster analysis method?**

Regarding **RQ2.1**, analysis from this chapter indicated that the common clusters found in the existing MOOC literature are indeed observed in entry-level MOOCs. Regarding **RQ2.2**, the results are more interesting. Analysis indicates that, in these specific entry-level MOOCs, traditionally underrepresented learners on the dimension of education level are more likely to sort into the commonly observed successful subgroups of All-rounders and Solvers compared to their better educated, disengaging peers. At the same time, these learners are also more likely to sort into the Auditing and Sampling clusters, potentially indicating a need for timely, targeted support. Further analysis seeking to understand the motivations of these learners would also be needed, in addition to a greater understanding of the top of the MOOC entry funnel, which, even among the entry-level MOOCs analysed in this chapter, was still disproportionately populated by already well-educated learners. Importantly, this pattern is not just an enrolment issue, either, as it persisted even when the learners were subset into committed learners who submitted at least one assignment. Regarding **RQ2.3**, results indicated that utilising a categorical variable like education level as a feature to derive clusters, utilising a distance measure like Gower (Ebbert and Dutke, 2020; Gower, 1971) may be a worthwhile approach to consider, especially if research is aimed to better understand how traditionally underrepresented learners are engaging with MOOCs.

5.7.1 Limitations

There are considerable limitations to this study worth noting that qualify the conclusions. First, using limited activity-based features constrained the analysis. Categorising total event counts into further specified activities like video-watching or peer-to-peer engagement could have made the clusters and the engagement descriptions richer. Second, the analysis could have been improved by considering whether the specific courses within the nine entry-level MOOCs analysed were associated with differential achievement and engagement, as indicated elsewhere in the literature (Ferguson and Clow, 2015). Third, limiting the cluster analysed sample to committed learners further narrowed the scope of the results and the claims that can be made, a common issue in learning analytic research (Gardner and Brooks, 2018). Conducting multinomial logistic regression with only one explanatory variable significantly limits the scope of what the analysis can claim. The bias resultant from selection into completing both enrolment demographic questionnaires and optional survey data represents another limitation to the analysis. Underrepresented populations, particularly along racial lines, have been found to be less likely to consent to engage in studies, as well as less likely to complete surveys, in web-based research. This means that the results could further reflect and embed those biases into the conclusions (Jang and Vorderstrasse, 2019). Furthermore, it is possible that more engaged learners were more likely to complete these questionnaires and surveys (Kizilcec and Schneider, 2015). Given that educational level was a variable used to cluster the data with the Gower distance metric, the inclusion of Unknown education level data renders two of the six Gower distance-based clusters defined by the property of their educational level being unknown. More sophisticated imputation methods could have been pursued and will be considered when submitting this work for publication. That said, including the Unknown education level data did not detract from analysis and led to a predictable outcome, discussed further in **Appendix 5.1**. Also, collapsing the 'Other' education level into Unknown is another limitation because this may have grouped some learners with a post-baccalaureate degree, such as doctorates, into a group with learners with far less education. Finally, analysing the SES data, for which there was only a small subset of data available from the USA alongside the full data set of 'committed learners' was potentially problematic insofar as the Gower Distance-based cluster results from the full data set could have differed from the Gower Distance-based cluster results from a USA-only data set. **Appendix 5.1** however, demonstrates this not to be the case. That such a limited amount of SES data was available however, is a limitation of the study.

6 BUILDING INCLUSIVE, ENTRY-LEVEL MOOCS: PERSPECTIVES FROM PRODUCERS

It isn't really prioritisation until it hurts.
– Unknown

6.1 Chapter Overview

This chapter presents the results of a qualitative study investigating how university MOOC producers building a series of entry-level courses conceptualise inclusion. **Section 6.2** provides a brief introduction and framing to the significance of these issues and summary findings. **Section 6.3** presents a review of the MOOC literature focused on producers. **Section 6.4** details the specific research questions, some methodological considerations, and the semi-structured interview methods and analytical procedures employed. **Section 6.5** presents and describes the results. **Sections 6.6** discusses the results and relates them to the existing literature. **Section 6.7** discusses the significance of the conclusions, and the limitations of this study.

6.2 Introduction

The information economy requires evolving knowledge and skills to secure economic stability (Autor, 2019; Meaney and Smith, 2016). Can MOOCs play a role in reducing educational and economic inequality by providing flexible learning opportunities to economically vulnerable populations, particularly populations without a tertiary degree? The answer to this question depends on whether MOOCs are designed in a way that effectively reaches and serves these populations. The prospect of doing so is no small task. Producing MOOCs moves beyond the solitary, instructor-centric, 'lone-ranger' modes of course design to include complex processes harmonising procedures and practices among a constellation of actors, including instructional designers and other technical staff (Chao, Sai, and Hamilton, 2010). While a surge of research into MOOCs over the past decade produced novel insights into the impact of course design on student behaviour patterns and outcomes, exploring the design and production processes employed by those creating the MOOCs, whom I call MOOC producers, remains a significant gap in the existing literature (Papathoma, 2019; Zhu et al., 2018a; Lowenthal et al., 2018).

The existing evidence of whether underrepresented learners utilise MOOCs successfully suggests that MOOC producers struggle to serve these learners. Studies have perennially confirmed that highly educated learners are overrepresented among MOOC enrolees and completers (Ganelin and Chuang, 2019; Meaney and Fikes, 2019; Hansen and Reich, 2015). Indeed, it has been suggested that, based on the past decade of research, universities and MOOC providers may be pivoting to frame MOOCs as continuing education resources for corporations and workers looking to upskill, without particular attention to the backgrounds of these learners (Reich and Ruipérez-Valiente, 2019). This pivot marks a sharp turn from the initial discourse surrounding MOOCs, which framed them as agents of educational democratisation (Hollands and Tirthali, 2014a).

From a normative perspective, this pivot could be troublesome. It could skew further the resources and production ecosystem of MOOCs toward designing scaled learning environments for learners less likely to be disadvantaged, a process termed hegemonic design bias, outlined in **Chapter 4**. Beyond the normative point, however, the pivot may be pre-emptive, as there remain less well-understood avenues of investigation into why MOOCs have struggled to meet their democratising mission. While MOOCs are generally considered not accessible to a wide variety of diverse learners, inquiry into the production processes of these MOOCs, especially from the perspective of producers creating them, is limited. These inquiries are especially important to consider in light of recent work suggesting that some intentionally designed, alternative forms of MOOCs can enable diverse learners to succeed (Lambert, 2020), as well as previous work indicating a gap between learning designers' intentions and MOOC students' experiences (Stracke et al., 2018).

Several papers have called for more investigation into the actors producing MOOCs and their design processes (Zhu et al., 2018a; Veletsianos and Shepherdson, 2016; Gašević et al., 2014). In this paper, a series of semi-structured interviews are conducted on a set of MOOC producers from a major research university in the USA. The interviews focus on how these producers are considering traditionally underrepresented learners and the challenges these students may face throughout the design process, probing the extent to which the producers' mindsets, practices, and processes take into consideration what underrepresented learners may need.

The interviews and analysis contribute several observations about the opportunities and challenges producers face in building inclusive MOOCs. First, diverse conceptions of inclusion reflect a sincere normative commitment on the part of the producers to make inclusive MOOCs, though the conceptions were quite distinct, making a coherent definition across producers hard to determine. Second, producers were intentional about utilising best-practice pedagogical methods, as well as innovative program design, to include as many learners as possible. Finally, innovative technology partners helped create interactive, unique experiences, but this also led to challenges in harmonising the design process and required the considerable influence of 'third-space' producers (White and White, 2016).

As specified in **Section 1.6.1** and **Section 2.2.1** comments about MOOCs more generally in this chapter refer to Coursera- and edX-style xMOOCs produced in the USA predominantly in English, and which stipulate open enrolment without entry qualifications, have no barriers to access content (though the content may be copyrighted and thus not meet the 'open' definition of OER), are online and available to anybody with an internet connection, and are free to complete though may charge a fee for certification (Deng et al., 2019). The interviews analysed in this chapter were conducted with MOOC producers from a major research university in the USA which hosts MOOC content on edX, further details of which are discussed in **Section 6.4.5** and **Section 6.4.6**.

6.3 Literature Review

In one of the first major reviews of the MOOC literature from 2013, Liyanagunawardena et al. noted that research on the perspectives of MOOC educators and producers were limited. This insight has been echoed several times since (Zhu et al., 2018a; Deng and Benckendorff, 2017, Veletsianos and Shepherdson, 2016; Gašević et al., 2014). Recent doctoral work from the Open University confirms this as well (Iniesto, 2020; Papathoma, 2019). While qualitative inquiry into MOOC producers has advanced in recent years, and will be considered, there are few studies focused on how MOOC producers consider designing virtual learning experiences in a way that may enable underrepresented learners to succeed.

Before examining the extant work on MOOC producers, it is important to situate this work in the broader literature of distance education, especially as it relates to the evolution of multi-stakeholder course design teams producing virtual learning experiences. I then review the literature on MOOC producers, followed by the somewhat limited literature on how MOOC producers design and build courses for underrepresented learners. I then consider the adjacent literature on MOOC design more broadly and some of the best practices the field has determined.

6.3.1 MOOC Production, Faculty and Producers

Examining the constellation of producers contributing to MOOC design and creation, and how this constellation developed historically, is beyond the scope of this thesis. Doing so would require a description of the 'bundling' and 'unbundling' of faculty roles in higher education through the specialisation of tasks and the simultaneous growth of professional staff aimed at achieving greater cost-effectiveness and improved learning outcomes (McCowan, 2017; Gehrke and Kezar, 2015; Tucker and Neely, 2010). Such a discussion spans from medieval times to the present. That said, a brief description is required to introduce several of the prominent actors in making MOOCs.

As John Scott recounts in his 2006 article *The Mission of the University: Medieval to Postmodern Transformations,* when universities emerged in the twelfth and thirteenth centuries, teaching students was the primary focus of faculty. Medieval Latin was the language of instruction, which students acquired before entering university. The printing press did not yet exist, so manuscripts, produced by scribes, were rare. Instruction was the opposite of innovative. Faculty members lectured over manuscripts and explained their contents, often including additional observations and commentary. This was done slowly and meticulously so that students could attempt to memorise the material. Small group debate among pupils and faculty allowed for more interaction and exchange, marking the frontier of pedagogy at the time. Crucially, however, this teaching and learning was faculty centric.

As universities rose in prominence, becoming central advisers to the Church and State as well as producing their scholastically trained administrators, and as universities helped lead the Renaissance in ushering in modernity, the tasks and duties of universities expanded. In the late 1800s in the USA, the grafting of the German research institute model onto the medieval scholastic college model fused the teaching and learning mission of the university with the more modern knowledge production function; thus, the prototype of the modern research university took form (Crow and Dabars, 2015). As complexity grew, so too did the responsibilities of faculty, trends necessitating increased administration and professional support staff (Scott, 2006).

Today, in traditional analogue higher education settings, two primary domains of work take place: an academic domain charged with teaching and research, and an administrative domain that provides operational support. Academic faculty typically balance research and teaching roles, and sometimes assume an administrative role such as a dean. These management roles are supported by professional staff in finance, human resources, and student services (Whitechurch, 2008). The tensions that faculty face in balancing these roles, especially between teaching and research, have long been noted (Fairweather, 1993; Feldman, 1987; Linsky and Straus, 1975). As universities continued to grow in complexity and participation in higher education broadened, even more activities were bundled into the faculty role, including counselling, advising students, and course development, for which many faculty had little training (Trout, 1979; Wang, 1975). Concurrently, concern began to simmer that if faculty were stretched too thin, they might become ineffective across all roles. Furthermore, there was a growing recognition that many university tasks simply necessitated specialised, professional expertise. Universities have started to unbundle these roles in the hope of improving learning and cost-effectiveness (Tucker and Neely, 2010). The emergence of educational technologies and virtual learning experiences extended this unbundling trend to the course development and instructional domain.

Because of their complexity, producing virtual learning experiences takes far more time than their equivalent analogue versions (Hollands and Tirthali, 2014b) and requires considerable expertise from multiple stakeholders (Chao et al., 2010). To create ten minutes of video, one study estimates six to eight hours is required (Hollands and Tirthali, 2014b). Various staff members must collaborate with faculty to produce high-quality distance learning experiences in what has been termed the division of labour for course development across "administration and logistics, course development, and student support" (Daniel, 2009). These roles are executed by staff Whitechurch (2008) terms "third-space professionals," who often blur the boundary between the academic and administrative domains. These dynamics are reflected and amplified in MOOCs, especially because of the high value placed on production quality, leading to such third-space roles as computer programmers, videographers, educational technologists, instructional designers, graphic designers, business managers, and other technical roles (Hollands and Tirthali, 2014b). There is no definitive arrangement or team structure for how a MOOC is produced. This will vary from university to university and depends on a number of factors, including which learning platform is used, where content is sourced from, what learning supports are provided, whether these functions are produced internally or externally, and funding considerations (Papathoma, 2019). Examples are provided in **Figure 6.1 and Figure 6.2**, which illustrate the complex series of actors involved.

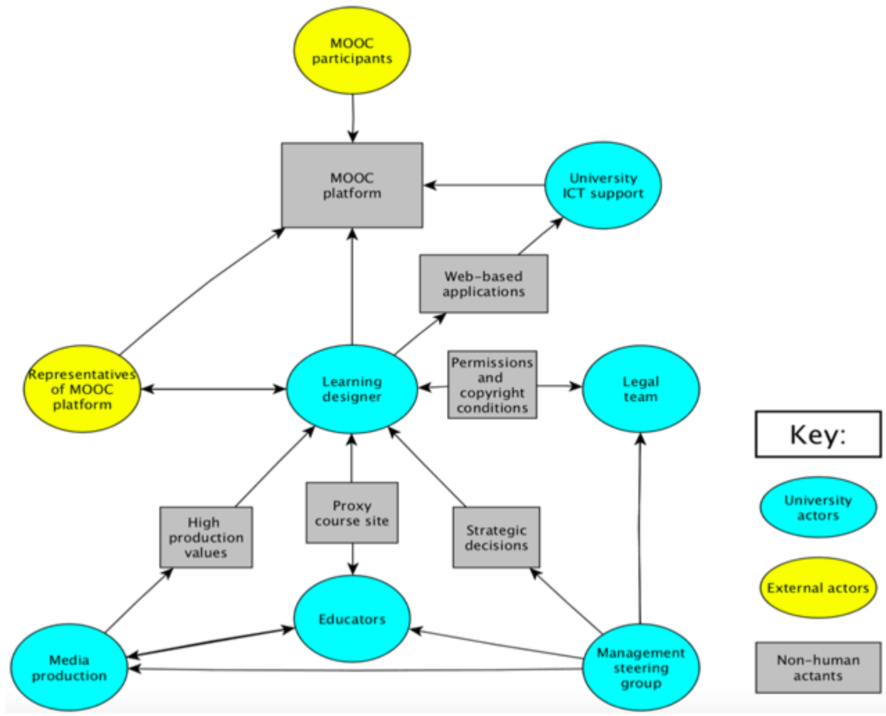


Figure 6.1: Visualisation of the various actors in the MOOCs ecosystem. From White and White, 2016.

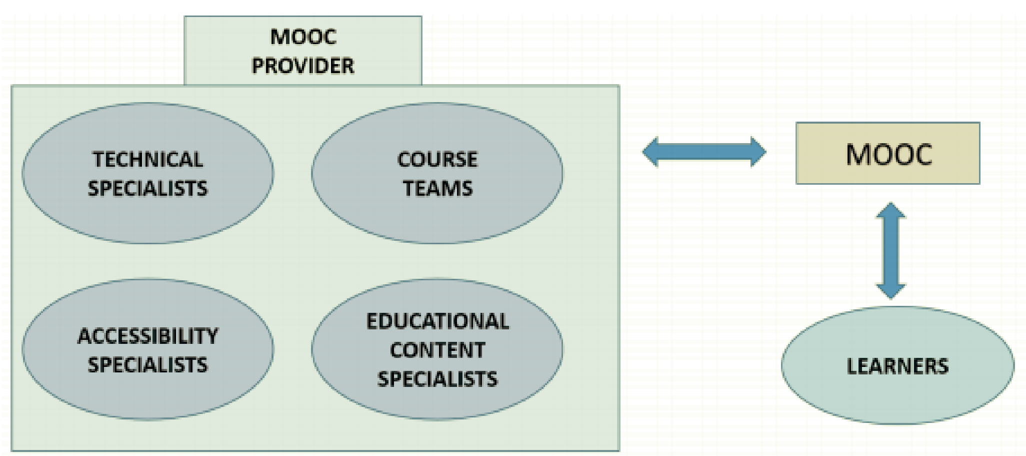


Figure 6.2: Visualisation of the various actors in the MOOCs ecosystem. From Iniesto, 2020.

6.3.2 Perspectives of Existing MOOC Producers

While there are many potential actors to interview to understand the mindsets, practices, and processes that underpin the production of MOOCs, most of the literature focuses on the instructors or faculty instead of the third-space actors who also contribute a vital role to the lifecycle of MOOC production. Most of these papers present a wide range of reflections: on the design and production process, but also on the overall experience of teaching a MOOC and the motivations for doing so, as well as speculation about MOOCs' implications on higher education. Few papers incorporate reflections on designing and producing MOOCs for an intended audience of underrepresented learners. The few that do are reviewed in the subsequent section.

In one of the more lucid publications on MOOC production to date, a group of academics from the University of Edinburgh reflect on their experience teaching a 'hybrid MOOC' that leveraged the pedagogical principles from cMOOCs in the context of an xMOOC (Ross, Sinclair, Knox, Bayne, and Macleod, 2014). This group of academics had straddled expertise across the disciplines of technology and education, so they were deeply familiar with the distance learning literature, had well-developed identities as online educators, and critically reflected on the MOOC design and production process throughout. They write:

> EDCMOOC was designed from a starting point of a belief that contact is what drives good online education. Our "Manifesto for Teaching Online"…culminates in this claim. Our MOOC's history, rationale, and design are all tightly bound to our identities as academics and our teaching philosophies... (p. 62)

The authors provide a detailed accounting of their processes. The course, however, was modelled on the Master of Science in Digital Education offered by the University of Edinburgh and thus calibrated to graduate-level learning.

In a 2015 mixed methods study, Evans and Myrick reported that instructors indicated excitement at the prospect of MOOCs in that they, in theory, might help learners access content who otherwise might not be able to do so, and to do so while interacting with a diverse community from around the world. The professors indicated concerns that the content might not be comprehensible for everyone, and that the lack of support might advantage the most well-educated learners. Some professors commented that they were concerned that MOOCs might be isolating. Others commented that making the courses took a great deal of time but that, overall, it was a rewarding experience (Evans and Myrick, 2015).

Haavind and Sistek-Chandler (2015) seek to better understand how MOOC instructors wear the many hats required of them by interviewing eight MOOC instructors across a range of settings, including cMOOCs and xMOOCs. Their primary finding is that instructors contribute to MOOCs through pedagogical design, which largely takes place during the planning and development stages of the MOOC. They therefore conclude that student interaction with instructors during the course is likely to have little overall effect on the student experience. They also note that MOOC instructors had limited training in producing the MOOCs. Additionally, the professors raised concerns about the difficulty of providing non-automated feedback to a large number of students, as well as security and privacy concerns related to distance education platforms.

Najafi, Rolheiser, Harrison, and Håklev (2015) interviewed eight MOOC instructors from the University of Toronto to better understand their experiences teaching a MOOC. They find that instructors were primarily motivated to teach MOOCs because of the expanded audience and geographic reach that MOOCs provided for their own teaching, echoing findings elsewhere (Evans and Myrick, 2015; Hollands and Tirthali, 2014b). The professors were also interested in the potential for pedagogical innovation, especially to devise ways that encouraged more active learning as well as ways to build learning materials that could apply to their on-campus courses. The instructors emphasise designing courses to stimulate higher levels of learning; specifically, application and integration of new knowledge, based on Fink's Taxonomy of Significant Learning (2013). This is a significant pedagogical intention, and as the authors note, "Instructional design that demands active learning, even within the realities of MOOCs, can offset the inherent teacher-centred design" (Najafi et al., 2015, p. 248). Najafi et al. (2015) also detail the structured approach taken to designing the course and the ample support that the instructors received from instructional design teams. The instructors were able to clearly articulate their desired learning outcomes, including for students to develop metacognitive, critical thinking, and inquiry skills, and begin to apply the knowledge they learn. The instructors also reflected on their intended audience, which they specified to be students that had little background knowledge with the course material. The course was ultimately taken by a population that skewed significantly toward the highly educated. While Najafi et al. (2015) explicitly call out the attempted scaffolding of assessment in the course, this focused more on the means of assessment (multiple-choice, followed by peer review) and less on how the content might have been scaffolded for diverse learners.

Blackmon (2016) interviewed eight professors to understand their perspectives on the future of MOOCs and their implications for higher education. Her primary findings relate to professors' speculations on the implications of MOOCs for face-to-face classroom experiences, the possibilities of student engagement and learning, using their expertise, expanding educational access, and other potential opportunities. Specifically, the professors diverged in their assessments of how MOOCs related to traditional classroom contexts, variously suggesting that MOOCs might replace large lecture classes or be used to enhance the learning experiences of these classes. They also noted that discussion boards provide an opportunity for real-time student engagement and feedback, and that MOOCs would enable professors to share their expertise with a wider audience. The professors are also largely optimistic that MOOCs could expand access to wider audiences, though they do not discuss the specific teaching and learning requirements to make this access meaningful for traditionally underrepresented students.

White and White (2016) present three case studies of interviews conducted with instructors and learning designers through a socio-technical perspective, including consideration of the third-space professionals as articulated by Whitechurch (2008). They find:

> …learning designers, occupy and define a hub-like, 'third-space' role which straddles academic and professional functions. Complex interactions with seemingly peripheral actors (legal, marketing, media production) shape the course design and development process, to some extent diluting or 'unbundling' the conventional 'jack-of-all trades' role of educators, or creating new roles required to satisfy organisational needs and priorities, or technical platform requirements. (White and White, 2016, p. 10)

Lowenthal et al. (2018) conducted a mixed methods study investigating what it is like to teach a MOOC, which included a survey of 186 MOOC instructors followed by 15 interviews. Instructors were motivated to teach MOOCs for three main reasons related to interest or passion, publicity and marketing, or benefits and incentives (Lowenthal et al., 2018). Professors were primarily motivated intrinsically by wanting to make a worldwide impact on students rather than by additional money or external motivations. Additionally, they found that most professors had “little online teaching experience and were new to teaching MOOCs,” (Lowenthal et al., 2018, p. 4), which echoes Haavind and Sistek-Chandler (2015), though Lowenthal et al. did note that the instructors were satisfied with their experiences overall. While sceptical that MOOCs would be as high-quality as face-to-face courses, most believed MOOCs could provide high-quality learning experiences. Instructors expressed great attention to designing and development of the course in advance, in part for fear of instruction not translating to scale and the potential real and reputational damage this could cause. At the same time, the focus on the design and development phase before the courses began made it difficult to adjust and adapt once the courses started. The instructors experienced some challenges with ensuring all materials were free and fell under the creative commons license, as well as some issues with video production.

Papathoma (2019) conducted 28 interviews of MOOC educators seeking to understand how these educators learn to teach. Her findings echo previous literature that the teams who make up MOOC educators encompass a wide variety of professionals with diverse contributions to the MOOC production process. Among these diverse stakeholders across different universities were a number of differing design and production models, each of which contained certain advantages and disadvantages. Papathoma found that when teams of educators shared clear goals and worked in a transparent manner they learned to teach most effectively.

6.3.3 MOOC Producers and How They Design for Difference

The qualitative work investigating the experiences and processes of MOOC producers provides insight into the perceptions of teaching a MOOC overall, with some exploration into the design considerations and production processes (Papathoma, 2019; Najafi et al., 2015; Ross et al., 2014). It is also clear from the existing literature that several different stakeholders contribute to this process and exert considerable influence in shaping design (White and White 2016; Hollands and Tirthali, 2014b). A smaller subset of papers from this genre focused on MOOC producers with a lens on the impact of MOOCs for underrepresented learners.

In a paper that reports on one of the more promising models of MOOC design for traditionally underrepresented learners, King et al. (2014) detail the design and production of a ‘fit for purpose’

MOOC, a concept originally detailed by Freeman (1991). The University of Tasmania's Wicking Dementia Research and Education Centre created the MOOC, which focused on how to care for patients suffering from dementia. The paper is notable because it explicitly details the design and production process of the MOOC, formally grounded in an open-learning design philosophy, with a pre-determined, explicitly defined underrepresented audience, and a meticulous design approach taken in order to accommodate the needs of that audience. The process considered "the impetus for attempting a MOOC design; the goal (desired outcomes); the nature of the content; assumed capability thresholds of the intended cohort and; the technical and pedagogical design implications of the cohort's learning readiness," (King et al., 2014, p. 108).

The MOOC producers determined that their audience would include students not qualified for tertiary education because of low academic and technical literacy. They attempted to ensure 'fit' between the knowledge they intended to disseminate and the capabilities of these learners by incorporating best practices from adult learning theory as articulated by Knowles (Knowles, Holton, and Swanson, 2014) and by utilising Laurillard's (2013) 'Conversational Framework' which proposes learning design to encompass six types of experiences: "acquisition, inquiry, practice, production, discussion and collaboration," (King et al., 2014, p. 113). This process is detailed in **Figure 6.3**.

Learning through	**Learning focus**	**MOOC platform technology functions**	**Desired Learning Outcome:** Learner can
Acquisition	Expert knowledge transmission (brain, disease, person)	Video interviews of experts accompanied by text transcripts; content summaries	Modulate own concept, observe teacher's practice
Practice	Student practicing knowledge	Body Central software, quizzes, learning activities (eg. scenarios/case studies) with hints and instant feedback	Apply core concepts learned and respond to feedback to improve actions (theory into practice)
Production	Student knowledge codified	Completing the final scene within MOOC family scenarios; recording notes in a reflective journal	Consolidate learning via articulating their conceptual understanding and how they have put it into practice
Discussion	Student sharing individual knowledge and perspectives	Thought tree responses to sentence stems. Discussion forums encouraging sharing of experiences, resources and research	Modulate own ideas and generate further ideas and questions

Figure 6.3: 'Fit for Purpose' Learning Design Strategy pursued in *Understanding Dementia* MOOC. From King et al., 2014.

Given that MOOCs typically involve minimal instructor-student interaction, a particularly unhelpful feature for students with lower academic abilities or fewer academic experiences, the producers focused on developing as many student-student and student-content interactions as they could, a hybrid of xMOOC and cMOOC pedagogy. Additionally, the producers sought to design knowledge acquisition experiences that focused on real-world, contextual examples and care-based case studies (suited to the many targeted students that were caring for dementia patients themselves). The content was developed with the explicit intention of meeting the affordances of students not eligible for tertiary education, and the content was reworked to include numerous real-life examples so that the learning connected with the students and could help them make sense of their lives, a core principle of adult learning theory (Caffarella and Barnett, 1994). The course was chunked into three units that spanned 11 weeks in total. Scaffolding was integrated early in the course, which included exercises to develop course navigation skills and familiarisation with online activities; sentence stems were also provided in discussion forums. The producers assumed that the learners would be more used to paper-based modes of learning, rather than digital interactive models, so they created content delivery to function as an interactive journal instead of content links to websites. They also ran a pilot of the study and iterated on their practices.

The ‘fit for purpose’ design was validated in a follow up empirical article (Goldberg et al., 2015). Students without a university degree were just as likely to complete the course as students with a university degree. More than 9,000 students enrolled, and the course had a 39 percent completion rate, far higher than the average MOOC completion rate.

A study by Iniesto et al. (2016) of the Open University finds limited progress in producing MOOCs that are universally accessible or that meet the needs of learners with disabilities. This work is continued in the PhD thesis published by Iniesto in 2020. The thesis included data from interviews with 26 MOOC producers across a range of roles, and a comprehensive accessibility audit focused on technical accessibility, user experience, quality, and learning design. The interviews unveiled several interesting findings. Iniesto notes that, while there is a consciousness about disability among MOOC designers, and some hope that massiveness might help build a bridge toward inclusiveness, the consciousness falls short of intentionally designing courseware to reflect this. Accessibility issues tend to be understood as related to physical disability concerns rather than other types of disability. Furthermore, the “priority is to meet the standards and legislation to avoid legal issues, and, so, MOOC providers do not think on accessibility as a service to the learner but as a means to meet the legislation” (Iniesto, 2020, p. 76).

Smith, Dowse, Soldatic, and Kent (2017) present findings from an interview with three academics with disability studies backgrounds who developed a MOOC that focused on disability. The interview highlighted that the nature of MOOC development was a fragmented and ad-hoc experience that presented challenges in aligning the resource needs and perspectives among the various stakeholders involved in the process. This echoes other findings from the general MOOC production literature of a diffuse and complex process that makes it difficult to intentionally design for specific learners (Hollands and Tirthali, 2014b).

Taskeen Adam of the University of Cambridge published two papers based on her PhD thesis work which focused on questions of inclusive MOOC design from the producer perspective. The first paper explores the lack of 'epistemic diversity' among MOOC providers in South Africa (Adam, 2020a). In conducting 27 interviews with MOOC designers, including 11 designers who were from Black and Multi-ethnic backgrounds, and 11 who were women, Adam sought to understand their open educational practices, and, specifically, "whose knowledges and what knowledges are forefronted" (2020a, p. 171). Adam finds that MOOC designers foreground how they understand the world, what they value, and who they are in the design processes. Adam underscores that these findings highlight the need for diverse MOOC producers that can reflect in a critical and productive manner on their positionalities and subjectivities. Adam then develops her conception of an 'embodiment of openness' to describe the way in which MOOC designers should approach their work. She asserts that the designers themselves ought to manifest a form of openness, as opposed to merely implementing their learned conceptions of open educational practices (Adam, 2020a, p. 183).

Adam's second article is based on the same 27 interviews and investigates how designers conceptualise injustice, and whether and how they attempt to account for this in their design (Adam, 2020b). Adam focused on a number of different dimensions of injustice in her analysis, including: "material, cultural-epistemic, and political/geopolitical injustices" (2020b, p. 2). Adam finds that different MOOC designers emphasised different dimensions of injustice in their own practices. Designers that were focused on epistemic and political injustice were primarily concerned with the colonial nature of knowledge production and pedagogical practices, and focused on transforming their educational practice to be relevant to their learners. This included not only integrating knowledge from pre-colonial Africa and including scholarship from the Global South, but also encouraging students to be critical of colonial knowledge based on their own experiences and contexts. The designers also noted the limited capacity they had to enact these epistemic interventions given that the MOOC platform was a technological artefact of the Global North. Furthermore, designers also expressed concern about material injustice, and some dissatisfaction with the discourse of decoloniality to address these concerns, with one designer noting that even if a country went “completely Albanian” (and kicked out all foreigners), it would be decolonised, but injustice would still persist (Adam, 2020b, p. 8). Novel interventions to support MOOC access in the context of material injustice were also noted; for example, making content downloadable as zip files and in low resolution, creating transcripts to serve those without meaningful access to video, and facilitating some of the learning through WhatsApp, a less data-intensive platform.

6.3.4 Other Considerations of MOOC Design

While there remains a considerable gap in the literature to better understand the design and production processes of MOOCs from the perspective of the people building the MOOCs, especially how they conceptualise doing so for underrepresented learners, the question of MOOC design itself has been analysed robustly. These inquiries have generally taken two forms. First, researchers have conducted heuristic analyses based on best practices of teaching and learning. Second, data mining and other quantitative studies have shed insight into the relationships between a number of MOOC design features and the impact on student behaviours and outcomes.

Early diagnosis of xMOOCs by distance learning scholar Tony Bates (2012) noted that they were predicated on an outdated, behaviourist pedagogy centred on knowledge transmission, devoid of the pedagogical experiences conducive to critical reasoning. This critical assessment was echoed in an analysis of the instructional design quality of 76 xMOOCs by Margaryan, Bianco, and Littlejohn (2015). The authors found that, while well-organised overall, MOOCs scored poorly on instructional design principles. There was little activation of prior knowledge for learners, few opportunities to integrate newly acquired knowledge, and little differentiation of materials for learners with different educational backgrounds.

Evans and McIntyre (2016) examine the course content of 65 humanities MOOCs to determine whether these courses could reach underrepresented students. They provide the following insightful assessment:

> Our examination found that 80 percent of professors noted that students required no previous background knowledge or experience aside from English proficiency. These course pages commonly included a description such as 'No background is required; all are welcome!' However, our study showed that the same course descriptions that included everybody-is-welcome appeals often qualified those statements by including specific abilities expected of students. For example, one Greek and Roman mythology course description said, 'No special background is needed other than the willingness and ability to synthesise complex texts and theoretical material'… Similarly, professors assigned challenging reading for students to understand… In fact, 82 percent of course descriptions mentioned some type of expectation of student preparedness, but 80 percent of those course descriptions also listed no prerequisites, potentially creating confusion about what professors actually expected of their students. (p. 318)

MOOCs may have low barriers in terms of technical access, but these low barriers may mask some cognitive and background knowledge barriers required for success in the courses. A 2018 survey on MOOC design supports these findings by reporting significant differences between learning designers' intentions and learners' experiences (Stracke et al., 2018).

Other studies have taken a more empirical approach. A key metric for engagement has been identified as participation in discussion forums, often leading to higher rates of student retention and higher grades (Coetzee, Fox, Hearst, and Hartmann, 2014). Designing discussion forums and other interactive components of MOOCs to be student-friendly may be a good place to start for increasing engagement. Evans, Baker, and Dee (2016) find that length of video is a stronger predictor of student engagement compared to the overall length of class. Pursel, Zhang, Jablokow, Choi, and Velegol (2015) further build the case for understanding student engagement as the best way to predict success in MOOCs. They find that high rates of engagement with videos and ungraded forums were predictors of completion.

Kizilcec and Schneider (2015) developed the Online Learning Enrollment Intentions (OLEI) scale to track user motivation in MOOCs. The scale was developed through an extensive and iterative process of pretesting, evaluating, and refining. They found that:

> …learners who enrolled because they aspired to a career change were more likely to watch more than 80 percent of video lectures and complete more than half of the assessments in the course. Whereas learners who enrolled due to job relevance seemingly sought to learn new skills or better understand a topic by watching a few lectures, those who enrolled for career change appeared to be more committed to learning a new skill or understanding new concepts to serve them on their new career path. (p. 6)

In a paper titled *Creating a Sticky MOOC*, researchers investigate a University of California San Diego MOOC called *Learning How to Learn* that received an average rating of 4.55 on a five-point Likert scale (Oakley, Poole, and Nestor, 2016). The researchers identify three primary factors that drove student satisfaction: instructor quality, conceptual clarity and importance, and format. The authors suggest these factors:

> …were achieved through the use of metaphor and analogy, instructor interactions with the graphics, the use of motion to maintain students' attention, tight scripting, a relaxed presentation demeanour, volunteer TA support, and relevant yet occasionally humorous quizzes. (p. 23)

These insights provide further suggestions for how to make MOOCs more engaging.

Nawrot and Doucet (2014) describe some of the difficulties students face in completing MOOCs. They identify time management as the biggest driver causing student attrition. This finding can be read as a broader part of the MOOC literature on self-regulation (Littlejohn et al. 2016; Davis, Chen, Jivet, Hauff, and Houben, 2016), suggesting that because of the asynchronous and often unstructured nature of MOOCs, students with higher self-regulating abilities may be better suited to succeed. Interventions to encouraging self-regulation, however, have been less promising (Kizilcec, Pérez-Sanagustín, and Maldonado, 2016).

Onah, Sinclair, and Boyatt (2014) test whether enhanced structural support would yield better student outcomes. Interestingly, while the students eligible to receive support did do better in the course than the comparison group, most students did not use the enhanced structural support. This outcome may be subject to opt-in bias; it is possible that the most motivated students opted for the more supportive class model.

René Kizilcec of Cornell University and colleagues have pioneered the use of large scale, randomised control trials on MOOC platforms to test several interventions targeted to particular populations of learners in order to improve outcomes.

Kizilcec et al. (2016) developed a self-regulation intervention derived from interviewing successful MOOC users and randomly assigned it to 653 students. The intervention was a series of recommendations for self-regulation (e.g., time-management strategies, goal setting, help seeking). While MOOC users reported finding the recommendations helpful, the intervention did not improve course persistence or achievement (Kizilcec et al., 2016).

Another intervention dealt with motivational framing. Kizilcec et al. (2014) tested three different strategies: a “collectivist” encouragement (“your participation benefits everyone”), an individualist encouragement (“you benefit from participating”), or a neutral encouragement (“there is a forum”) (Kizilcec, Schneider, Cohen, and McFarland, 2014, p. 14). The encouragements were found to be ineffective in motivating learners to participate in the forum, and the collectivist encouragement was found to discourage contribution relative to the other two (Kizilcec et al., 2014).

Kizilcec, Saltarelli, Reich, and Cohen (2017) attempt an intervention specifically on achievement gaps in international contexts. The intervention addressed ‘social identity threat,’ or the fear of being seen as less capable because of one’s identity. The authors describe the impetus for the study in the following manner:

> Social identity threat can impair working memory, learning, and performance (and contribute to academic achievement gaps based on students’ race, gender, and social status). Brief psychological interventions have been shown to improve performance of members of identity-threatened groups in the USA, such as African Americans and women in male-dominated fields. (Kizilcec et al., 2017, p. 251)

The intervention was tested on users from lesser developed countries (LDC) in a randomised controlled trial. The authors found:

> Although the affirmation had a consistent positive effect for LDC learners, it had a negative effect in more developed countries (MDC) learners in the replication experiment. Prior research suggests that affirmation can cause disengagement, particularly for those who are not under psychological threat or who see little possibility to improve. (p. 252)

A similar study was conducted in China, focused on lower-class men in an English-language MOOC as an at-risk group. The intervention led to improvements in grades, persistence, and completion rates (Kizilcec, Davis, and Cohen, 2017).

Kizilcec et al. (2020) tested a number of these interventions across a range of contexts applied to a wide variety of learners. Disappointingly but importantly for the evolution of the field, they find that many of these interventions do not work at scale across a wide variety of learners in different contexts. Even well-designed interventions targeted to enhance value-relevancy or improve self-regulatory strategies are perhaps less widely applicable than previously hoped, implying a greater need to discover supportive approaches for contextually heterogenous populations with differing needs (Kizilcec et al., 2020).

6.3.5 Literature Review Synthesis, and Opportunities to Contribute to the Field

A literature review analysing 46 studies representing more than 440,000 learners by Lambert (2020) investigates the question of whether MOOCs have contributed to broadly conceived notions of equity and inclusion. Lambert notes that, while traditional MOOCs from major providers like Coursera and edX have repeatedly struggled with equity and inclusion, a number of alternative design approaches have yielded positive results. In her assessment she includes the ‘fit for purpose’ design approach taken in King et al. (2014), as well as other approaches designed with a particular focus on underserved student groups (Wang et al., 2018). These alternative designs often included explicit dimensions that provided enhanced support, including face to face support, digital support, and study groups. Lambert notes that “what seemed to matter most was the intentional and collaborative design for disadvantaged cohorts” (Lambert, 2020, p. 1).

The Lambert (2020) paper focuses on one of the original animating questions of this thesis project: how might institutions of higher education provide inclusive learning opportunities at scale to traditionally underrepresented groups? Lambert holds that such designs are possible when intentionally crafted and collaboratively executed.

Much of the literature on MOOC production does not investigate these claims nor even really consider the possibilities. Instead, researchers have provided insights into instructors' perceptions of teaching MOOCs and their motivations for doing so (Najafi et al., 2015), the challenges associated with MOOCs (Hollands and Tirthali, 2014b), speculation about their implications for higher education (Blackmon, 2016), and overall experiences teaching and developing them (Haavind and Sistek-Chandler, 2015; Evans and Myrick, 2015). The literature does indicate some evidence that the processes of producing MOOCs map onto the diffuse and complicated processes of producing other digital experiences in higher education, with third-space professionals exerting a considerable influence (White and White, 2016; Hollands and Tirthali 2014b). These professionals' perspectives are often not explicitly sought, investigated, nor addressed in the literature.

Regarding concepts of inclusion in the design process of MOOCs, three papers provide detailed, though substantially different, insights stemming from diverse perspectives. The King et al. (2014) paper details very pragmatically the way in which a 'fit for purpose' cohort MOOC was designed and how it was successful. Iniesto (2020) reports that producers consider disability passively and somewhat inaccurately, with an emphasis on meeting the demands of legislation rather than the needs of learning. The set of papers from Adam (2020a; 2020b) focuses broadly on the mindsets of MOOC designers and, specifically, how they consider and reflect notions of inclusion in their practices, and the resultant design interventions enacted in response to these reflections. The sources of disadvantage, however, are framed as epistemic and socio-material, and less specifically about different learning and content acquisition needs.

Additionally, it should be noted that throughout the literature, the emphasis on intention and goals as being important to successfully designed MOOCs is clear (Papathoma, 2019; Ross et al., 2014; King et al., 2014). Furthermore, some examples indicate that MOOC designs can be successful for underrepresented groups, if these learners are specifically considered during the design process and designs that enable these learners are implemented (Wang et al., 2018; King et al., 2014).

In this context, the aim of my investigation emerges. First, more work needs to be done not only to understand the MOOC producer perspective in general, but more specifically the mindsets, processes, and practices undertaken by these producers when designing and building MOOCs. In particular, understanding whether considerations of underrepresented learners are incorporated into these processes and practices at all, and how these considerations are defined and conceptualised, will be a valuable contribution to the literature. Doing all of this in the context of the USA makes these insights more useful, as little producer research has focused on this context. Second, it is critical to sample from a variety of MOOC producers; at present, faculty and MOOC instructors are overrepresented, and the important perspectives and processes of the third-space professionals are worthy of deeper consideration. Finally, given the ample amount of instructional quality and empirical work on the design of MOOCs, it would be insightful to know whether MOOC producers are making use of these insights to inform their practice. This would be especially interesting to know considering the noted research-practice gap between the learning analytics research community and its complementary practitioners (Buckingham Shum et al., 2019; Bakharia et al., 2016), as well as a well-noted research-practice gap with virtual learning experiences in general (Price et al., 2016).

6.4 Methods

In this section, the specific research questions, framed and motivated by the literature review, are explicitly stated. Then, I briefly consider some of the ontological, theoretical, and epistemological dimensions arising from my proposed questions. The ethics of conducting this research are then considered. Then, a description of the specific research method is articulated, including the interview technique the interview protocol utilised, the data collection methods, interview context and participants, and well as the analytical processes followed.

6.4.1 Research Questions

The research questions are derived from the literature review synthesis in **Section 6.3.5,** which highlighted the opportunity to investigate how MOOC producers consider underrepresented students when building courses, and to do so in the USA, and among a wider range of MOOC producers than previously included in much of the literature. Therefore, my primary research question, which can be further specified into two sub-questions, is as follows:

- **RQ3: What pedagogical and technology design strategies are useful to employ in attempting to build inclusive MOOCs and similar virtual learning experiences?**
  - **RQ3.1: How are MOOC producers conceptualising inclusion for the students that will use the courses they are building?**
  - **RQ3.2: What processes and practices are they engaging in toward producing inclusive MOOCs?**

6.4.2 Ontological and Epistemological Considerations

One common pitfall of qualitative work is that ontological and epistemological considerations are not explicitly made (Braun and Clarke, 2006). This is true of the qualitative MOOC literature reviewed in this paper, except for the doctoral dissertations. A more thorough accounting of the ontological and epistemological assumptions forms part of **Section 2.5** of this thesis; that section delves into the multimethod design of this thesis project, and how the various component parts are harmonised. For this chapter specifically, it is worth rearticulating some of those points.

There is no definitively agreed-upon framework for conducting qualitative research. It is both art and science, and subject to several factors and constraints based on the research questions. That said, some broad approaches have been delineated in the literature. Braun and Clark (2006) describe two camps, the first being tied to specific theoretical and epistemological assumptions and exemplified by a method like Interpretive Phenomenological Analysis. The second camp is independent of theoretical and epistemological constraints; tools that fall into this camp, like thematic analysis, represent a method that can be applied to a wide range of investigations. Iniesto (2020) and Iniesto et al. (2016), among others, conduct thematic analysis of their qualitative MOOC data. I take a similar approach.

While collecting and analysing qualitative data, I attempt to remain bounded by empiricism. The approach taken follows what is considered a post-positivist (Phillips, 1990), subtle realist (Hammersley, 1992) ontology and epistemology. Thematic analyses of interview data are utilised to determine themes describing the processes and practices of the MOOC producers. I try to stay close to the data in my analysis, seeking to illuminate the reality described according to the producers, and how this may relate to the existing literature or emergent themes from the producers. The analysis does not seek to infer, extrapolate, or attribute ideological meaning or significance beyond what is explicitly stated. I take a primarily inductive, semantic approach in analysing data (Braun and Clark, 2006), to not allow my assumptions to overly influence the coding and analysis of the data, as well as to avoid the ontological and epistemological quandaries inherent to interpretivist, relativistic approaches (Maxwell and Mittapalli, 2010; Hammersley, 2009). This means I try to analyse the literal meaning of the data, and aggregate codes, themes, organising themes, and global themes into accurate reflections corresponding to what the participants explicitly said or intended. This also means that I will not ascribe unstated motives or mechanisms or postulate theories as being made manifest in the data. At the same time, in accordance with a post-positivist, subtle realist approach, I recognise that I am not wholly separate from the research, data collection, or analysis processes, and thus inevitably my own lenses and biases shape my interpretation of the data (Braun and Clarke, 2006; Attride-Stirling, 2001). In qualitative analysis, these lenses and biases enter every phase of research, from constructing the interview questions, to the interviewing technique, to the transcription process, and beyond, whereby the researcher imposes meaning onto the data (Lapadat, 2000). Braun and Clark, whose 2006 paper on thematic analyses serves as a primary methodological reference for this chapter, expound upon the challenges of qualitative work in a recent interview. They note that their paper is intended to be a starting point for reflective practice rather than a gospel set of rules to be followed. They urge researchers to approach thematic analysis with flexibility and openness, suggesting that qualitative approaches should be bespoke to particular types of data, research questions, and methods considered (Braun, Clarke, and Hayfield, 2019), all selected and imposed by the researcher. Indeed, I have tried to integrate this insight into my own approach, fusing analytic methods from Braun and Clarke's seminal paper (2006), with another seminal paper on thematic network analysis by Attride-Stirling (2001). The approaches complement each other, enabling rich methods to discern and describe themes (Braun and Clarke, 2006), followed by an approach that helps construct basic themes, organising themes, and global themes (Attride-Stirling, 2001).

6.4.3 Theoretical Motivations

In **Chapter 4** on hegemonic design bias, key socio-technical levers embedded in the MOOC production ecosystem are identified as candidates for sources of bias that may inhibit MOOC design from serving the users most in need. One of those levers is the complex process of how MOOCs are made, involving multiple stakeholders, operating under different constraints and with different incentives and goals. If MOOCs are to be designed in an inclusive way that democratises learning, as was originally hoped, a more adequate accounting of the design process is required.

These insights stemmed from existing literature reviews of MOOCs, framed by broader discussions of the socio-political and socio-technical dynamics of technology construction. Specifically, as the literature review in this chapter uncovers, there remain gaps in understanding the specific processes and practices implemented by producers of MOOCs seeking to design courses that can serve underrepresented communities, and the extent to which these processes and practices are done intentionally and explicitly, and whether they draw from academic literature to do so. Borrowing the Socio-technical Interaction Network (STIN) lens from social informatics (Meyer, 2006), these questions can be properly understood as neither explicitly technical nor explicitly social, in order to avoid the optimism of techno-determinism as well as the vagaries of more critical strands of social research (White and White 2016; Meyer, 2006). This perspective is buttressed by Langdon Winner's (1980) work on the politics of technology, which describes how the structures of technological artefacts act as a way of settling an issue, meaning that design dictates usage by whom and for whom, regardless of intent. In my interviews, I focus on the personal backgrounds of the subjects, as well as the environment in which they are conducting the interviews. Alongside this, I ask specific questions regarding the technical production process. This balance aims to reflect the challenge of designing MOOCs as neither an explicitly technical nor explicitly social process.

Additionally, while this chapter began prior to the full conceptualisation of hegemonic design bias, one feature of the meso level of that conceptual framework developed in **Section 4.5.2.2** is worth noting: specifically, the research-praxis gap. This phenomenon is what it sounds like; there is a gap between the research and the practitioner community. While this gap is well documented in the academic literature more broadly (Bero et al., 1998), in the virtual learning environment literature more generally (Price et al., 2016), and among the learning analytics community specifically (Ferguson and Clow, 2017; Bakharia et al., 2016), its specific application to MOOC producers is less understood.

6.4.4 Ethical Considerations

Section 3.4 described the various important ethical decisions made while producing this thesis. There are a few pertinent issues to call out as they relate to my qualitative study.

First, this study was approved by the research ethics processes of both the University of Cambridge and the host university in the USA. These approvals are appended to this thesis as **Appendix 3.1** and **Appendix 3.2**.

Second, and most significantly, I made the decision to redact all personally identifiable information regarding my participants, out of a conservative and strict intention of duty of care, in consultation with my supervisor. As the MOOC producers are working professionals, it is important to ensure as close to absolute anonymity as possible, as the content of these interviews contains sensitive and personal information. I do include significant detail about educational experiences and previous work experiences, but only those intimately familiar with the host institution would find these details pertinent to a person.

I redact all information specifying the university that hosted me. This seeks to further safeguard the participants' anonymity. Additionally, I redact all names of corporate partners and technology providers, so as to not disclose sensitive information, as well as to further safeguard the participants' anonymity. The only noteworthy exception is for edX, the MOOC platform. As the scope of my project focuses primarily on Coursera- and edX-like xMOOCs, by far the largest providers of these kinds of courses in the USA, including that detail did not risk disclosing identifying information.

All interview subjects signed a consent form, included in **Appendix 3.3**.

6.4.5 Semi-structured Interview Protocol

Interviewing is a common technique employed across qualitative research on MOOCs, as it allows for the perspectives of various stakeholders to be captured (Papathoma 2019; Lowenthal 2018; Iniesto et al., 2016). Semi-structured interviews specifically are deployed when the researcher asks a series of questions that are pre-determined yet open-ended (Ayres, 2008).

Semi-structured interviews are valuable for several reasons (Barriball and While, 1994). First, this research is exploratory in nature and deals with the potentially sensitive explication of perceptions and opinions; semi-structured interviews are less formal and potentially less fraught as a result and enable probing and clarification throughout the dialogue. Second, the research questions are broad and are motivated by terms like inclusion and access, all of which are perennially conflated, confounded, and contested in the academic literature; it is not expected that the MOOC producers interviewed are academic specialists, and they therefore are unlikely to have a common vocabulary and understanding of these terms. Finally, semi-structured interviews do not require the exact wording of each interview question to be the same across interviews (Barriball and While, 1994). This is useful for a number of reasons as a) probing and clarification questions are likely to be different across the sample, b) the tenor, ambience, and the direction that the interview takes is likely to be different across the sample, and c) as a person with a stutter, the flexibility enabled by the semi-structured interview is particularly beneficial for me, as fluency with words varies highly according to the situation, day, time, and a number of other inexplicable reasons.

I structured my interview protocol, represented in **Figure 6.4,** to elicit two dimensions about the producers: their personal history and context for how they ended up in their role, and their specific thoughts regarding whether and how they design for inclusion and the processes and practices they employ to do so. I wanted to understand the lived experiences that shaped the producers, as well as the specific processes and practices influencing their work. Additionally, and importantly, I did not specifically define underrepresented or inclusion for the producers. I left these terms unspecified to not unnecessarily lead the interviewees.

Finally, this was an iterative process. At the time of my original interviews, I thought motivation and engagement as constructs were going to feature more significantly in my work. I moved away from this but have left the interview guide intact as it was delivered. Similarly, I included equity as a term when I started this process. I have since removed it because the term has taken on such charged and malleable meaning, and I focus on inclusion instead; nevertheless, I left the interview protocol as delivered.

A pilot study conducted in the summer of 2017 allowed for testing and refinement of the interview protocol research questions. Two outcomes of the pilot study were particularly informative of the subsequent final study. First, the pilot interviews were overly formal and inflexible, stifling the arc of natural dialogue. As a result, I reconsidered the delivery of my protocol so that it still generated the data of interest but in a way that allowed for a more authentic flow. I thus erred on the side of informality and rapport-building during the interviews. Second, I needed to better incorporate the role of marketing and user acquisition into the MOOC discussion; this is a much deeper and more complex dialogue than I realised, and resulted in prompt seven. Additionally, I encountered several logistical hurdles that informed my subsequent interviews. The digital education unit within the host university houses both traditional online courses as well as MOOCs. It became apparent when coordinating these interviews to specify the intention of interviewing people working directly on the MOOC program. As working professionals, the participants were very busy, so the time of one hour was considered to be potentially too long. The pilot interviews confirmed however that one hour, while ample, did provide sufficient time to explore issues deeply and that a half-hour may have felt rushed. Thus, the interviews remained at one hour.

1. How did you become involved in making MOOCs?
    a. Were you excited by this prospect?
    b. Did you have much experience with technology previously?
2. When making your MOOC, who do you envision as the end user?
    a. Is this different or similar to your standard student?
    b. Do you consider that MOOCs might be used by traditionally underrepresented users?
    c. Do you consider 'equity' or 'inclusion' as a design constraint?
    d. Did you consider your own biases that you may be unintentionally embedding in the design?
3. What learning and pedagogy theory do you reference when making MOOCs?
4. Do you focus on engagement and motivation during the design process? If so, how?
    a. What theories of engagement and motivation do you reference?
    b. Is there other academic literature you reference?

5. What are you most proud of regarding the MOOCs?
    a. Has working on the MOOC been an overall positive or negative experience?
6. What would you like to see improved with MOOCs?
7. What is the user acquisition process?

Figure 6.4: Semi-structured Interview Protocol.

The interview protocol was designed to elicit answers aligned to the specific research questions articulated in **Section 6.4.1**, as well as the theoretical motivations considered in **Section 6.4.2**.

RQ3.1 reads, "How are MOOC producers conceptualising inclusion for the students that will use the courses they are building?" Questions one and two, including the sub-questions, were asked in reference to this research question. Question one, which probed about the producers' background experiences before engaging in the MOOC production process, was included in light of the discussion of technology production as containing both social and technical considerations (White and White 2016; Meyer, 2006). Understanding the producers' personal background was intended to deepen understanding of the social dimensions that may explicitly or implicitly inform the design and production process. Question two more directly aligns with the explicit intent of RQ3.1 by inquiring whether and how the producer considered underrepresented students and their potential learning needs in the design and production process of the MOOC.

RQ3.2 reads, "What processes and practices are they engaging in toward producing inclusive MOOCs?" Questions three and four, including the sub-questions, were asked in reference to this research question. Questions three and four are informed by the literature review and **Chapter 4** on hegemonic design bias; specifically, that while ample research literature exists on best practices for designing MOOCs, there is a noted gap between research and practice in the virtual learning experience community (Buckingham Shum et al., 2019; Bakharia et al., 2016; Price et al., 2016).

Questions five and six were included as open-ended, reflective questions that could further inform **RQ3.1** and **RQ3.2.** Question seven was included in reaction to the pilot version of this study, in which the user acquisition of learners emerged as a key design and implementation consideration among the producers.

The semi-structured nature of the interviews (Barriball and While, 1994) allowed for probing and clarification throughout the interview to occur organically. As will be discussed in the results, the ways in which the producers collaborated with each other and with other external actors emerged as a key theme in the interviews, and many of the extemporaneous questions and follow-up comments provided insight into these collaborations.

The overarching research question undergirding the interview protocol, the specific research questions, and this chapter in general, was motivated by the literature review in **Section 2.3**, in which it was identified that MOOCs have struggled to reach traditionally underrepresented learners in higher education. RQ3, which reads, "What pedagogical and technology design strategies are useful to employ in attempting to build inclusive MOOCs and similar virtual learning experiences?" was pursued for this purpose.

6.4.6 Data Collection Procedures and Participants

All interviews took place at the host university during April 2018 and lasted for about one hour. Interviews were recorded, and notes were taken during the interview process. Interviews were professionally transcribed and checked for accuracy. Additionally, interview participants were provided with the opportunity to review the recording and transcript to ensure accurate transcription of their thoughts. Interviewees were emailed a copy of the transcriptions and audio files and made minor typographical corrections or corrections for clarity. These were tracked as changes on the document and reviewed and accepted. Two interviewees made no changes.

The transcription process itself is extremely theory-laden and an interpretive act; whether to transcribe text verbatim, including all disfluencies and utterances, how to represent pause length, the way to capture conversational moves, how to represent body language and tone of voice, among a potentially infinite list of considerations to make, all impose a researchers' epistemological orientation into the research process (Lapadat, 2000; Lapadat and Lindsay, 1999). Unlike discourse or conversation analysis, where standardised transcription conventions have developed, such as the Jefferson system, thematic analysis does not require the same level of detail as it is primarily concerned with the content of the interview (Braun and Clarke, 2006; Lapadat, 2000). A thorough verbatim account was transcribed, which included all verbal utterances (e.g., uhs and ums were included) so as to as closely as possible retain all information in the verbal account true to form (Braun and Clarke, 2006). This followed a modified orthographic approach, which Edwards (1993) describes as not requiring specialised linguistic training, “relying instead on extensions of a code which readers of English already know” (p. 20). More detailed considerations described by Edwards (1993), like the contours of intonation, syllabic prominence, and non-verbal events or actions, were excluded.

There is no single producer or designer of a MOOC. Instead, several different groups of people contribute to their production (Iniesto, 2020; Papathoma, 2019; Hollands and Tirthali, 2014b). My interviews focused on producers embedded within the university and included Professors, Instructional Designers, and Program Managers. The six interviewees were purposively sampled. There was an element of convenience sampling as well (Teddlie and Yu, 2007), resultant from the various availabilities of participants willing to be interviewed.

All interviewees helped construct a series of entry-level MOOC courses; specifically, on a sequence of courses that collectively represent entry-level university credits for first-year students. Producers were interviewed with the understanding that the content discussed reflected their own opinion and experiences, and did not represent the views of their employer. My sample contained one Professor, two Instructional Designers, and three Program Managers, indicated in **Table 6.1**.

Table 6.1: Interview Sample

Interview Role	Value
Professor	1
Instructional Designer	2
Program Manager	3
Gender breakdown, Male: Female	4: 2

Professors are responsible primarily for content development (Najafi et al., 2015; Hollands and Tirthali, 2014b). They typically set the goals and objectives of courses, usually modelled off the on-campus versions they teach. Professors are typically the instructors of record for MOOCs and are usually employees of the university producing the content of the MOOC. I interviewed one Professor.

Prof. Smith holds a PhD in Computer Science. He previously taught robotics and embedded systems at a private, for-profit technical university. His research focuses on computer science teaching and how it can be improved upon for more learners. His teaching quality has been recognised by a half dozen awards for excellence. He is a Senior Lecturer in the School of Engineering and teaches an introductory programming MOOC. The course teaches problem-solving through computer science techniques. Students gain exposure to algorithmic problem-solving principles and how to write basic programs using modern programming languages. Prof. Smith is a white male in his mid-30s.

Instructional Designers play a dynamic role situated between the content developed by the Professor and the online architecture that allows MOOCs to run (Hollands and Tirthali, 2014b). Instructional Designers help transform traditional academic content into online versions. They work extensively with professors, as well as the technical teams at MOOC platforms like edX, to ensure that usability meets high standards while maintaining fidelity to the content. They influence the content, user experience, and user interface decisions. They are the intermediaries between the offline and online academic worlds. These Instructional Designers are usually employees of the university producing the content of the MOOC. I interviewed two Instructional Designers.

Ms. Thomas holds master’s degrees in English and Instructional Design. She worked for five years as an English teacher before entering a variety of roles focused on technology implementation in higher education. This included significant time working for private, for-profit online universities as an Instructional Designer and faculty member. She helped develop an extensive array of classes as an Instructional Designer in what would be considered a third-space producer role at my host institution. She oversees a robust portfolio of online courses, including several advanced MOOCs for MicroMasters degrees. Additionally, she helped develop several courses on economics, business, math, and engineering. Most of these courses began as a part of the traditional online offerings of the host university and were being adapted to MOOC versions at the time of the interview. When interviewed, Ms. Thomas was an Instructional Designer, and now serves as the Lead Instructional Designer. Ms. Thomas is a white, middle-aged female.

Ms. Underhill holds a master’s degree in Instructional Design. She worked as an elementary school teacher for five years before entering technology in higher education. She worked for a few years in private, for-profit online education in secondary and postsecondary settings before moving to the host university as an Instructional Designer, a third-space producer. Ms. Underhill was a comparatively junior Instructional Designer at the time of the interview. She had helped develop courses in social work and nursing before becoming involved in the MOOC effort. Ms. Underhill is a white female in her 30s.

Program Managers do not have a significant role in the content development of MOOCs, though they are prominent third-space actors. Their role is essential for a few reasons. First, they are usually responsible for dealing with the politics of MOOC development: a constellation of stakeholders, from university presidents and professors to for-profit and non-profit technology companies, have different incentives and desires regarding the production of MOOCs. Program Managers are usually tasked with balancing budgets, timelines, production schedules, marketing, and envisioning new iterations. These Program Managers are usually employees of the university producing the content of the MOOC. Program Managers were not prominently featured in the existing literature on MOOC development. I interviewed three of them.

Mr. Valek was, at the time of the interview, a Program Manager for technology integration and is now the Senior Director of Technology Integration for Learning, where he oversees technology partnerships, advises on technology architecture, and helps design and implement prototypes and systems for the entry-level MOOC initiative. Mr. Valek was a third-space producer in his position intersecting program management and technical system design. He helps manage the various corporate technology partners working on the courses. He has a background in computer programming and technology consulting. He entered the world of online education as a consultant for a leading non-profit online education provider specialising in competency-based education before moving to the host university. Mr. Valek is a middle-aged white man with a bachelor's degree.

Mr. Williams was, at the time of the interview, a Manager for Data Systems for the host university and is now the Head of Advertising and Data, where he oversees user acquisition for digital offerings. As a third-space producer, Mr. Williams has deep experience and expertise in digital marketing. He holds a bachelor's degree and a master's degree in Management. He began his career as a Supply Chain Analyst at a major multinational company before entering the field of digital marketing, serving as a Vice President of Monetisation to a start-up before joining the host university. He is a white male in his 30s.

Mr. Anderson is the Director of Student Services and is helping build a student success centre prototype for the entry-level MOOC program at the host university. He is a third-space producer. He holds a bachelor's degree and a master's degree in Business Administration and brings extensive experience in student services for online higher education to his role, having previously served for more than a decade building out the student services function for a major private, for-profit online university. He is a white, middle-aged male.

6.4.7 Analytical Process

NVIVO qualitative analysis software was used to code and collate my findings (Richards, 1999). To analyse my data, I combined two common approaches to thematic analysis, the first from Braun and Clarke (2006) and the second from Attride-Stirling (2001). Each individual technique could have been sufficient. Braun and Clarke (2006) however, offer more concrete guidance in coding data and working codes into themes, whereas Attride-Stirling (2001) provides constructive guidance in creating thematic networks. This allowed for a more systematic accounting for and derivation of themes. Specifically, I followed the first five steps of analysis from Braun and Clarke (2006) and the last four steps articulated by Attride Stirling (2001). Table 1 below positions Braun and Clarke (2006) and Attride-Stirling (2001) side by side for comparison. The steps in bold in each column reflect the processes I followed.

Table 6.2: Braun and Clarke (2006) and Attride-Stirling (2001) Thematic Analysis Methods.

Braun and Clarke (2006)	Attride-Stirling (2001)
1. Familiarise yourself with the data	1. Code Material
2. Generate Initial Codes	2. Identify Themes
3. Searching for themes	**3. Construct Thematic Networks**
4. Reviewing themes	**4. Describe and Explore Thematic Networks**
5. Defining and Naming Themes	**5. Summarise Thematic Networks**
6. Producing the Report	**6. Interpret Patterns**

I familiarised myself with the data over the course of 2018-2020. I took notes during my interviews which allowed me to capture initial thoughts and sentiments that would inform my codes. I reviewed the transcripts to ensure the accuracy of transcription and took further notes at this stage. Once I felt familiar with the data, I assigned initial codes to the entire data set. A total of 83 codes were developed and were assigned to 1,223 segments of text. Following the framework proposed in Braun and Clarke (2006), a semantic, rather than a latent, approach to developing codes was applied, meaning that the codes were developed directly from the text rather than imposing a theoretical framework. Segments of text could be coded multiple times, and there was no limit on how many codes could pertain to a segment of text to remain faithful to the fluidity and potential contradictions within the data corpus (Braun and Clarke, 2006).

While saturation is a notoriously vague and difficult component of qualitative work (Guest et al., 2006), and while the present study could have benefitted from a larger sample, I do believe thematic saturation was achieved, in a local sense (rather than a global, statistically sound, or externally validated sense, as described in **Section 3.5**). Specifically, the interviews themselves were narrowly focused and lasted for about an hour each, generating ample text. After applying 83 codes to the corpus of text, no additional data could be further developed into a separate code or category (Glaser, Straus, and Strutzel, 1968). I then reviewed the codes and formed initial intuitions for themes (Braun and Clarke, 2006). This process comprised of looking at text segments organised by code, rather than the interview transcript, allowing me to abstract initial intuitions for broader themes from coded text segments based on salience or commonalities. I took notes on what was discussed at each code and utilised these notes to group common codes into initial themes, striving to have initial themes be distinct enough not to be repetitive but broad enough to capture ideas contained across coded text segments. I refined these initial themes over time for clarity and simplicity, condensing them where possible, ultimately deriving a set of 16 themes that I named and defined as basic themes. I then grouped basic themes into organising themes based on shared issues discussed, and then finally grouped organising themes into global themes, which summarised the main assertions reflected in the organising themes (Attride-Stirling, 2001). The global themes, organising themes, and basic themes serve as the primary units of analysis presented in the results.

Each thematic network is structured around a global theme. Three global themes were identified, each comprised of two organising themes. Each organising theme was comprised of between two and four basic themes. Certain themes that were more prominent than others will be noted in the thematic network figures, as well as in the analysis. Furthermore, differences across the global themes, particularly as they relate to occupation-specific sorting of the producers across organising themes, are also noted when these occur.

Table 6.3 contains the specific steps taken to analyse the data for this project. **Appendix 6.1** contains the codebook, which illustrates these steps in greater detail. **Appendix 6.1** has also been redacted in line with the ethical considerations discussed in **Section 6.4.4** and **Section 3.4.**

Table 6.3: Thematic Analysis Procedures.

Analysis Phase	Analysis Procedure	Citation
1. Familiarise yourself with the data	• Take notes during interviews; review interview notes; transcribe data; take notes during transcription; re-listen to interviews, take notes.	Braun and Clarke (2006)
2. Generate Initial Codes	• Define codes and label data based on literal meaning of text; when possible, define code with terms explicitly from text. 83 codes applied to data set to 1223 segments of text in my data.	Braun and Clarke (2006)
3. Searching for themes	• Review notes, review codes, begin to collate codes into potential themes; check against other codes and other initial themes. 24 initial themes were identified.	Braun and Clarke (2006)
4. Reviewing themes	• Generate initial set of themes, and begin process of refining those themes, condensing where possible, and checking against codes and other themes. 16 final, refined themes identified.	Braun and Clarke (2006)
5. Defining and Naming Themes	• Generate clear definitions and names for each theme.	Braun and Clarke (2006)
6. Construct Thematic Networks	a) Arrange themes b) Select Basic Themes c) Rearrange into Organising Themes d) Deduce Global Theme(s) e) Illustrate as thematic network(s) f) Verify and refine the network(s) • 16 basic themes, 6 organising themes, and 3 global themes identified	Attride-Stirling (2001)
7. Describe and Explore	• Clearly name and define each set of organising themes, and global themes; synthesise insights for each, and	Attride-Stirling (2001)

Thematic Networks	illustrate with supporting evidence from interviews.	
8. Summarise Thematic Networks	• Construct clean, clear figures to present the thematic networks, and describe overall insights derived from the interviews.	Attride-Stirling (2001)
9. Interpret Patterns	• Link thematic network to research questions, existing literature, points of interest in relation to MOOC production, and recommendations for future research.	Attride-Stirling (2001)
Total Interviews	6	
Text Corpus	35,256 words	
Codes Derived	84	
Initial Themes	24	
Basic Themes	16	
Organising Themes	6	
Global Themes	3	

6.4.8 Analytical Validation

To validate the thematic analysis an inter-rater reliability process was followed. Approximately 22.2 percent of the text corpus was shared with a fellow PhD candidate well-versed in qualitative methods; he was asked to select the accurate corresponding basic theme relating to the quote. A total of 98 quotes of text were provided, alongside two randomised basic themes and the correct basic theme corresponding to the quote. Substantial agreement was observed, with a computed Cohen's Kappa of **.831,** indicating strong agreement (McHugh, 2012), indicated in **Table 6.4.**

Table 6.4: Inter-rater Reliability Assessment.

	Value
Observed Agreement	87/98 = .887
Probability	1/3 = .333
Cohen's Kappa	(.887 - .333) / (.667) = .831

6.5 Results

Thematic networks themselves are not analysis; they are tools of analysis (Attride-Stirling, 2001). In this results section, each global theme is introduced, and its corresponding thematic network is described and explored, detailing the meaning of its component organising and basic themes. Illustrative examples of text from the interviews themselves support this analysis. Basic themes will be detailed more granularly. The number of specific producers to mention or expound upon a basic theme will be discussed. This also allows me to highlight which, if any, of the basic themes that make up an organising theme were more prominent than others. This is reflected in the thematic maps as well; the most prominent basic themes for each organising theme are outlined in bold in the thematic network diagrams and made explicit in the analysis. I reserve more observations and comments for the discussion and conclusions sections. Finally, all basic themes were discussed by at least three interview participants.

Quotes are reported verbatim, with light edits for clarity and readability, following common conventions (Lingard, 2019; Corden and Sainsbury, 2006); these include, for example, the deletion of duplicate phrases, as well as 'uhs' and 'ums,' but no such words or phrases that provided meaning to the text. Furthermore, as discussed in the ethical considerations in **Section 6.4.4** and **Section 3.4**, the host university, the name of its MOOC program, and all corporate and technology partner names, with the exception of edX, have been redacted and replaced with generic descriptions in brackets to preserve anonymity (Lingard, 2019; Corden and Sainsbury, 2006).

6.5.1 Global Theme 1: Diverse Conceptualisations of Inclusion

The thematic network for Global Theme 1 is depicted in **Figure 6.5**. Producers revealed diverse conceptualisations of how they considered inclusion during the design process, often articulated explicitly and attributed to various motivations. Additionally, these conceptualisations were informed by several different personal and professional sources. These conceptualisations were often quite broad and included many different dimensions of disadvantage experienced in educational processes by various underserved populations.

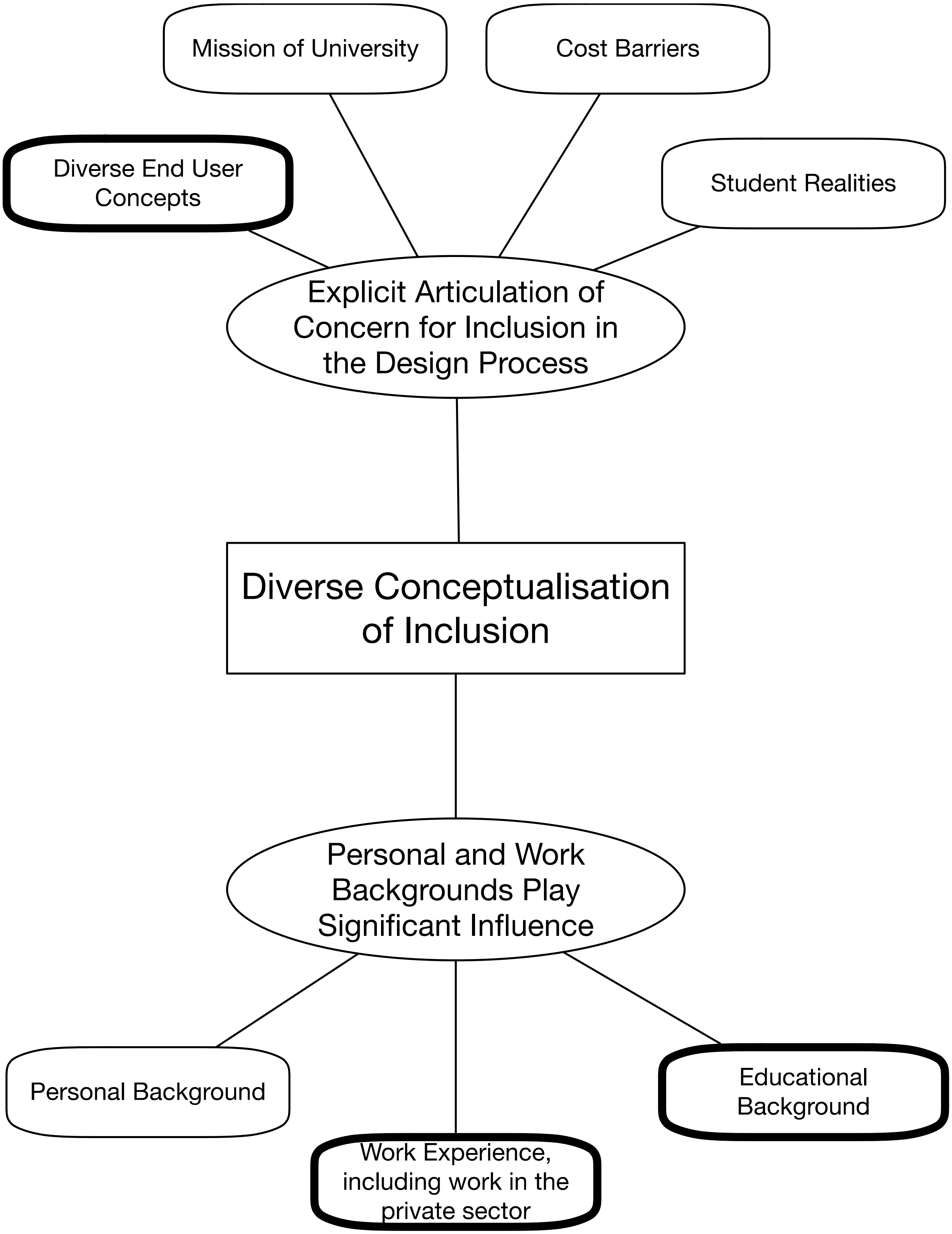


Figure 6.5: Thematic Network for Global Theme 1: Diverse Conceptualisations of Inclusion. Note: Basic themes circled in bold reflect more prominent basic themes.

6.5.1.1 Organising Theme 1.1: Explicit Articulation of Concern for Inclusion in the Design Process

Producers explicitly articulated different versions of what inclusion meant to them and indicated a broad array of motivations for considering inclusion in the way they did. The explicit articulation of inclusion, and the differing motivational framings, were originally identified and categorised as basic themes and were eventually grouped together into an organising theme. The key feature across this organising theme was an explicit articulation of a commitment to inclusion in some manner. The following basic themes, beginning with the most prominent, comprised this organising theme, each exemplified by a quote or quotes from the interviews.

- **Diverse End User Concepts:** Six of the six producers articulated broad and diverse descriptions of who they consider to be their end-using student, with some discrepancies among them. This was a theme explicitly commented upon by each interviewee, making it the most prominent basic theme in this organising theme. No other theme was mentioned as consistently by each producer. The quotes shared reflect an expansive array of end user concepts. The dimensions of underrepresentation are diverse, extending well beyond not having a tertiary degree and being from a lower socioeconomic background.

  Ms. Underhill, the relatively more junior Instructional Designer, said:

  > I think of everybody… I know we have had students who went through our [MOOC Program] because they didn't have the qualifications to get into [host university] online. So, they use [MOOC Program] as a pathway to get into [host university]. Women who have children or families. All that. So, I just kind of think of – I encompass everybody. I don't want to discriminate between – people with ages between 18 and 27 – I just think of everybody.

  Mr. Williams, the head of advertising and data of the program, conceptualised inclusion for the students they were serving as:

  > You know, I'm interested in looking at factors like single mother, if they are a working adult, if they are older than 26 sort of types of learners that need more flexible designs

> to support their learning and that don't sort of make up the mean learner that people think about.

Mr. Valek, a different Program Manager more focused on technology integrations, said:

> We will use [MOOC Program] to allow them to earn their way in. These are highly motivated students.

Prof. Smith, the PhD Computer Scientist who built an introduction to programming course, stated:

> The people that are looking for a career change, they're already successful they already know how to college so to speak yeah and have already developed those study skills. But we also know that there's people that are going to be in the class that have none of those skills…And we expected sort of middle-of-the-road high school math education.

- **Mission of the University**: Five of six producers described the institutional commitment of the university to providing high-quality educational experiences to as an inclusive definition of learners as possible to be inspiring and motivating. This was the second most noted motivation cited for the diversity of end users that producers had in mind when building their MOOCs. While not as prominent as the diverse end users theme, this was still an important finding that was identified, and will be considered more in the discussion. Prof. Smith, the PhD in Computer Science who concentrated on building an introduction to programming course, stated:

> Yeah it's like it's part it's our part of the mission statement right —…it's about who we include — and that's one of the most heartening things about working for [host university] is that it — especially in [MOOC Program] — that is like core to how [host university] works and it's super exciting.

Mr. Anderson, charged with building a prototype version of the student success centre, said:

> It is big. Honestly, it is giving people the opportunity to succeed that otherwise wouldn't have it.

Ms. Underhill, the more junior Instructional Designer, expressed:

> But I think that something – that was exciting to me was the global audience aspect and just making education accessible for all, which I feel is really [host university]'s kind of mission.

- **Cost Barriers to Higher Education:** Four of six producers discussed the high-cost barriers to higher education. The risk this imposes on students was as a design constraint for how they built their programs. In this basic theme, producers focused on wanting to help learners reduce their opportunity cost and lower the risk of starting. Ms. Thomas, the lead Instructional Designer, explained:

  > Give them that kind of early perspective at a low cost and see if it's that like interesting to them, low risk, low cost. And they could take it for free and audit it and see if that's what they want to do.

  Mr. Williams, the head of advertising and data, noted:

  > And we know that that's important for students to be able to keep their eye on the price to get to the finish line.

  Mr. Anderson, the third-space producer leading the student success centre prototype, said:

  > Giving everyone that wants an opportunity to get a degree, that opportunity at a reasonable price that's not going to put them in debt until they're forty-five or fifty.

- **Realities of Student Life (Non-Financial)**: Three of six producers discussed stories of real students, and the various challenges and barriers they face and overcome, as a source of inspiration and design orientation. This was the least mentioned basic theme cited. The stories did, however, reflect end user conceptualisations based on real people with real needs who were underrepresented, which directly informed the producers. Mr. Valek, the technology integration Program Manager, noted:

  > There are certainly students that have personal backstories. There are some students — we had a person go in our [MOOC Program], it was a lady that had started college, and in her first term her father died. He was the breadwinner for that household, and she had to; she couldn't withdraw, she got like a 1.0 or something. She was no longer — she had to take like a couple years off and work. After that she tried to get back into

> college and they're like "you have a 1.0, no." So very intelligent young lady, once she was able to take these classes she got like straight A's. And she's now getting straight A's at [host university].

Similarly, another producer shared a striking story that shaped how they approached design. Because it included sensitive material, the quote will not be reproduced nor attributed to an individual. It was a story about a victim of sex trafficking who abused drugs and struggled with school. Later in life, when she was in safer and better circumstances in which she could begin to thrive, she found out about the host university's MOOC program as a potential pathway to the university and subsequently enrolled.

6.5.1.2 Organising Theme 1.2: Personal and Professional Background Play a Significant Role

Beyond the explicit articulations for inclusion mentioned, there was an additional organising theme that was identified as part of this global theme; specifically, the personal, educational, and professional backgrounds of the producers played a significant role in how they conceptualised inclusion and why they did so. Personal, educational, and professional backgrounds were originally identified and categorised as basic themes themselves. These themes, with corresponding evidence from the interviews, include the following.

- **Work Experience, Including Private Sector Experiences:** Six out of the six producers mentioned an array of work experiences, including considerable time in the private sector and at for-profit colleges, as providing ample lessons and cautions that informed their practice. This was a particularly prominent basic theme in this organising theme and is considered further in the discussion. Ms. Thomas, the more senior Instructional Designer, noted the following when discussing how her previous work experience at a for-profit college shaped how she thought about the challenges high-need students have in navigating information asymmetries in the higher education landscape:

  > They marketed the commercials during the times that population was home. So between soap operas, as cheesy as it sounds during like when Maury Povich was on so they, on purpose, would buy that time slot from three to five and then at night too. So

> they... that was just where students were seeing those commercials and they, you know, and they were in that mindset of “I don’t want to end up like these people on this talk shows.” So then, boom, here’s comes the commercial and the commercials were amazing because, of course, the person that is being interviewed was a single mother who went back to school, who now is working at this place.

She later noted how the for-profit experience shaped her pedagogy:

> And I feel like when I got to the for-profit, it was the same thing, very behaviourist. There is very little community of learning. You just repetition, repetition, repetition, and know that they thought learn, practice, apply was this great learning theory and a great way, but it was not learn, practice, apply. It was apply, apply, apply and you keep taking the clues until you passed or you keep taking that class over and over until you passed or you figure out how to pass, you figure out how to cheat so you can pass.

- **Education Background:** Six of six producers cited academic backgrounds in education or subject matter expertise as informative to their approach, making this too a prominent basic theme. Educational experiences, both formal and informal, typically provided producers one of two things: technical backgrounds required to make MOOCs, or a language and consciousness around differentiated learning needs that contributed to how they approached inclusive design. Ms. Underhill, the more junior Instructional Designer, for example, had recently attained a degree in educational technology that significantly informed her practice, primarily through the technical skills it enabled her to use, though she was also a former teacher.

> So, I looked into working as an ID [Instructional Designer] and went back to [host university] for a degree in ed-tech. And at that time, they had two tracks. One ed tech for classroom teachers and ed-tech for Instructional Designers. So, I took the ID route.

Prof. Smith, the Computer Scientist, meanwhile, had an important experience with a MOOC that informed his approach to interactive pedagogy.

> My experience was — I was looking at this and my ideal was — I took a class on a particular set of artificial intelligence algorithms from [Corporate Entity]… And it was taught by [Professor]… It was taught by him and it was one of those hands-on a whiteboard type video courses so it was all of him like drawing on the whiteboard and

> talking over it but all of his videos were super short and it would go straight from like — he at the end of every video you'd be like now you try and do this and it would take a screenshot of that last frame and that would be the illustration for a little project that you do and you'd implement some code and it would give you feedback on how well you did.

- **Personal Experiences and Values:** Three out of six producers explicitly discussed personal experiences or personal values as drawing them to a career in education and for committing them to inclusion. This was not as prominent as other sub-themes in this organising theme. For Mr. Valek, the technology integration Program Manager, his personal inspirations were particularly motivating for him.

> I am inspired by Gandhi – yeah Gandhi was all about supporting the masses right like don't leave the masses behind. And we — it's so easy to try to just look for the upper echelon of our culture but we need to really take a step back and say we all win if we support all of humanity. And so, with that in mind we have to look at education as how can we do this for everyone. And it's only being exacerbated as we move forward into a digital age that requires this knowledge.

6.5.2 Global Theme 2: Innovative Pedagogy and Program Design

The thematic network for Global Theme 2 is depicted in **Figure 6.6.** Beyond conceptualising broad and diverse notions of inclusion, the producers took several very concrete steps to make their program designs and MOOC courses inclusive. Producers explicitly expressed philosophies of teaching and learning aimed at enabling diverse students to succeed, including the utilisation of best practices and innovative pedagogical strategies, as well as innovative program design. Unlike the previous global theme, where all six producers were represented across all organising themes and the most prominent basic themes were based on discussion from all producers, the organising themes in this global theme take on a more occupation-specific dimension. The Instructional Designers and Professor contributed to the teaching and learning organising theme, whereas the Program Managers contributed to the program design theme. One Program Manager, who oversaw technology integration, contributed to both. The occupation-specific sorting is considered more deeply in the discussion.

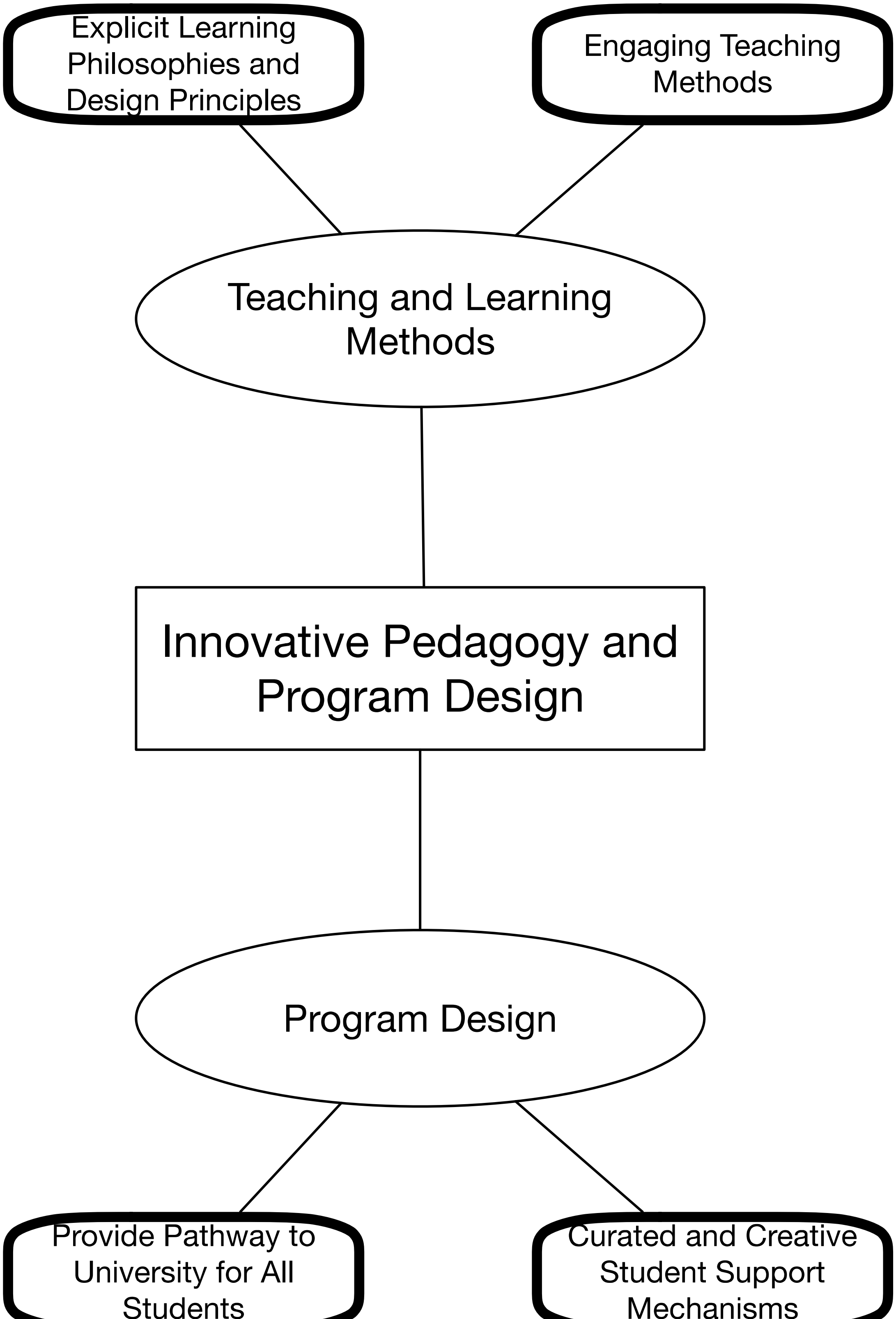


Figure 6.6 Thematic Network for Global Theme 2: Innovative Pedagogy and Program Design. Basic themes were equally prominent, though with an occupation-specific sorting.

6.5.2.1 Organising Theme 2.1: Teaching and Learning Methods

Several basic themes related to teaching and learning methods were identified in the original coding and analysis process. These themes were aggregated into the teaching and learning method organising theme and were comprised of the following, with corresponding illustrative evidence from the interviews. This organising theme was primarily reflected in comments by the two Instructional Designers, the one Professor, and the technology integration Program Manager.

- **Explicit Learning Philosophies and Design Principles:** Three out of the six producers explicitly detailed their teaching and learning philosophies as guiding how they built their courses, often explicitly mentioning frameworks and strategies to account for the different abilities of various learners. These comments came specifically from the two Instructional Designers and the Professor. Ms. Thomas, the senior Instructional Designer, commented that she considered herself and her pedagogical approach to be constructivist (Piaget and Elkind, 1967), as opposed to the more rote, behaviourist learning perspective (Skinner, 1963).

  > I... when I was looking at where I align myself, I definitely was more in the constructivist kind of realm because I wanted to start with that foundation and you build that foundation and, you know, you then create the next, the next, then you scaffold off of each other; it's a big buzzword right now but that community of learning, learning from each other, and select from the instructor, like I would try as much as I could to get the students to learn from themselves.

  Prof. Smith, who led the programming course, described the active learning philosophy he took to building his class as follows:

  > You only learn by doing. So, we wanted to make the class very much focused on — you watch something you read something you do something. And you do that over and over and over — a hundred times before you get to the project and then you do something again.

- **Engaging Teaching Methods**: Four of six producers sought to embed numerous examples of engaging content into their courses, including real-world relevant course content, interactive pedagogy, peer-to-peer learning opportunities, and personalised and adaptive instruction. In addition to the Instructional Designers and Professor, the technology integration Program Manager also made comments reflected in this theme. Prof. Smith, the Computer Scientist charged with building a programming course for a wide array of learners, discussed the concept of ‘industry moments,’ which explicitly linked learning content to real-world application.

> It was it was in the midst of it. One of the things that we put in our original design was industry moments. The idea was to tie whatever it is that they’re learning right now to what is useful and what is used in industry and to put a face on it. And that’s kind of like the treat at the end of every major section. We did a bunch of visits to some computer history museums to show some cool stuff about how we got here and then it’s like we did some career stuff at the same time and so they’re usually – one or two little videos at the end that are that are like that kind of like Discovery Channel, you know inspirational personal stories type of things.

Mr. Valek, the technology integration Program Manager, similarly felt compelled to create course experiences that related to the real world.

> Or writing classes that focus on LinkedIn, how to write a resume, and how to write a cover letter, and how to design a website. Things like that that will cross both real-world skills and start that process of academia. So, we are working on choosing content that will be giving them wins and give them real skills that are usable today.

6.5.2.2 Organising Theme 2.2: Program Design

Several basic themes related to program design were identified in the original coding and theme aggregating process. These themes were aggregated as an organising theme reflected in comments made by the three Program Managers and were comprised of the following.

- **Provide Pathway to University for All Students:** All three Program Managers interviewed discussed the innovative design of the overall MOOC program. The MOOC program provided an opportunity to earn formal entry to the university if certain criteria were met; this is provided as an alternative pathway to admission, even for students initially denied. Mr. Valek, the technology integration Program Manager, succinctly summarised this innovation, which enabled the university to formally not deny any student who applied.

> So, what this is, students that would otherwise be denied admission to [host university], we say you take these four classes or eight classes depending on your age and we will guarantee you can get into [host university]. So, we're no longer going to deny any students to [host university].

He later continued:

> You take the class — if you prove that you've done it, then you'll go through our admit process. But you there is no admit process to take these classes. We let you take them for free. You only pay when you pass. And then if you pass four at the appropriate grade point level, we will pass you off to admissions.

Mr. Williams, the head of advertising and analytics, described the pathway options as follows:

> So we call it qualifying transfer. Because the program qualifies them and then if they do meet basic requirements they can transfer into something else. So recap: [Corporate Partner Program], [MOOC Program], [host university] Online not accepted, on ground denies, and this q and t population (qualify and transfer).

- **Curated and Creative Student Support Mechanisms:** Three of the six producers, all three program managers interviewed, described various student support mechanisms implemented to enhance the user experience, from adaptive emailing techniques and pleasing user interface design, to a formal student support coaching infrastructure (in early development at the time). Mr. Anderson, who was the director of student support services for the university's traditional online program as well as a prototype version of the student support system for the entry-level MOOCs sequence, discussed his approach to user experience.

  > You want them to go through this user experience and it looks like [host university], it feels like [host university] and they're excited about coming here and they can navigate through the whole process with minimal clicks. Like you don't want it to be too complicated, you don't want to move to click a million times… So, it's things like that where it's engaging for the student, it's modern, it's a simple but brilliant design that's going to capture your audience and keep them engaged because that's the other part.

He continues to describe the prototype student success centre coaching:

> So shorter conversations, not as in-depth, not delving much into the student's you know personal life and juggling the time commitment, it's really a lot of time informing about the programs since this is something new that no other school is doing. It's hard to have an elevator speech to explain it to people that are like 'okay you're not admissible to [host university] right now but there is this set of programs that we have for you that we tell you about it.'

6.5.3 Global Theme 3: Operational Practices and Processes, Influenced by Third-space Actors

The thematic network for Global Theme 3 is depicted in **Figure 6.7**. In addition to implementing innovative pedagogy and program design, several operational practices and processes contributed to attempts to design courseware and programs in inclusive ways, often in practices and processes that highlighted the influence of third-space actors. For various reasons, these practices and processes both enabled inclusive design and could make it more challenging. The third global theme shares similarities to and contrasts with the first two global themes. In contrast to the first global theme, where there were more prominent basic themes across both organising themes (for a total of three out of seven registering as prominent), four of the five basic themes in the third global theme registered as prominent based on comments from all producers. As with global theme two, however, the one theme that was less prominent across this thematic network did have an occupation-specific dimension, which will be considered in the discussion.

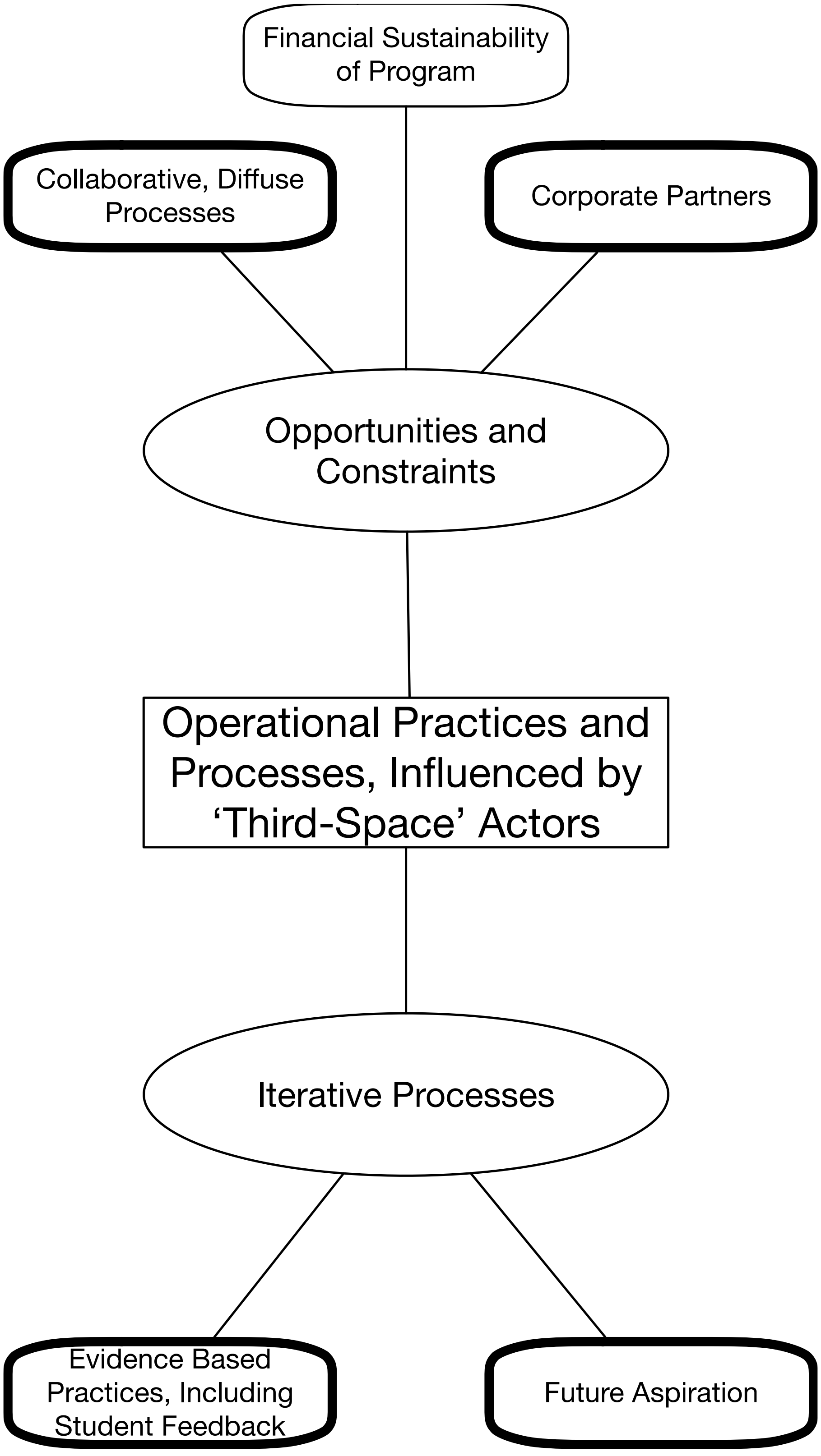


Figure 6.7: Thematic Network for Global Theme 3: Operational Practices and Processes, Influenced by Third-space Actors. Note: Basic themes circled in bold reflect more prominent basic themes.

6.5.3.1 Organising Theme 3.1: Opportunities and Constraints

Specific opportunities and constraints, particularly as they related to corporate partnership models both within and outside the university, were identified as basic themes, which were then later aggregated into this organising theme. The first two basic themes reflect more prominent themes in this organising theme. These basic themes are identified below and illustrated through quotes from the interviews.

- **Corporate Partners**: Six of six producers emphasised this basic theme, though in different ways. Extensive corporate partnerships, from platform and curriculum providers to employee benefits partners, were an integral feature of MOOC and program construction, presenting both opportunities and challenges. In an example of some of the challenges that could arise from reliance on external tools, Ms. Thomas, the Instructional Designer, described some of these limitations.

  > We try things that [host university] Online has, [Corporate Technology tool], is one of them. It incorporates fantastically in [Corporate platform] not too much in edX. So we've been leaning away from [Corporate technology tool].

  In this example, a beneficial curriculum tool is described as having high efficacy when integrated into one of the university's formal online offerings. When this tool is integrated into the open-scale platform hosting the MOOC program, the tool works less well and has been de-prioritised as a result.

  Separately, there was ample detail provided of corporate partnerships that help serve employee benefit opportunities. Because of the sensitive nature of these partnerships, more explicit details are not provided. The general insight, however, is that working with external corporate partners was not just a manner of integrating technology into learning but entailed extensive programming to enrol and support lower- and middle-skill workers earning degrees.

- **Collaborative, Diffuse Processes:** Six of six producers described producing the MOOCs as requiring substantial collaboration within the university and external partners. As with the first basic theme, this was identified as both providing challenges and opportunities. Prof. Smith, the Computer Scientist leading the programming MOOC, responded thusly when asked about the process of acquiring students, exemplifying the diffuse processes:

> I have no idea.

Similarly, Ms. Thomas noted.

> I know with [our MOOC] – edX does our advertising like that's part of our contract with them, and I don't know how they do.

The collaborative nature of their work, however, also had several constructive elements. Ms. Underhill, the more junior Instructional Designer, described the productive reciprocal nature of her relationship with the professors when designing MOOC courses.

> At the same time, I'm also not a subject matter expert, so I am also putting trust in these faculty members who do teach daily to teach students. But also, like I said, as an advocate for the student, I feel I have to explain to our faculty members, at times, remind them, "okay this is not your typical run-of-the-mill course." So, I think that's a conversation that we have often with our faculty members throughout the development process.

- **Financial Sustainability of Program:** Three of six produces explicitly discussed the financial sustainability of the program, which is reflected in this basic theme. This was not as prominent as the first two basic themes. Additionally, there was an occupation-specific dimension; the Program Managers were the producers who considered this prominently in their work, though this was not the case for the Instructional Designers and Professor. Simply put, the MOOC program needed to be financially sustainable over the long run. The program needed to eventually be self-sustaining. Mr. Valek, the technology integration Program Manager, described this goal as part of his work.

> I've also helped on finding the value proposition so that we could make this a financially feasible endeavour that [host university] could have work long-term.

Many more specific insights were provided about the ways in which these producers discussed this theme but were sensitive in nature. That said, the important insight was that, for the program to be sustainable in the long run, the revenue earned by fees for certification and credit needed to amount to the costs of running the program.

6.5.3.2 Organising Theme 3.2: Iterative Processes

Beyond the opportunities and constraints amidst various collaborations, several basic themes were identified that pointed to the iterative nature of the design approach. Notably, the use of data and feedback were instrumental throughout the processes and practices. The basic themes that comprised this organising theme, all of which were prominent, are described here, along with illustrative examples.

- **Evidence Based practices, Including Student Feedback**: Six of six producers described how the extensive use of data, student feedback, and intentional reflection on what was successful is incorporated. For example, when describing a portion of the success coaching strategy he is helping to prototype, Mr. Anderson explained:

  > So, we know for example if the student is going to leave the university, it's usually going to be within the first four classes and to look at it as a line graphic, it usually happens in the first or the second class. If it doesn't happen in the first or the second class then it's the third or the fourth. If we keep them beyond the fourth session, it goes drastically down.

  Ms. Underhill, the Instructional Designer similarly expressed:

  > It's really hard, especially with MOOCs. If they're going to drop out, they do it within the first two weeks.

  Prof. Smith, leading the programming course, explained how data helped him define goals for this course.

  > And it's like they're going to wait— they're going to post a question on the discussion boards and they're going to wait six hours before they see an answer. That that's the average time. And that's really good, that's fantastic right. I'd love that to be minutes instead you know.

- **Future Aspirations**: Six of six producers discussed expansive future visions of the program. A general commitment to continuous improvement as well as ambitious future product and program iterations were common. Prof. Smith, who led the programming course, exemplified this ethos.

  > So, there's there are all these ideas that are sort of floating around right now, people are trying all these radically different things and we've just like scratched the surface with our pretty pictures and interactive things, which is still a big step forward for computer science. So, there's a lot of stuff that we want to try to do.

  Mr. Valek, the technology integration Program Manager, said:

  > We need to have more performance pathways. And focus more on making sure students that come to us, that we can support them in being successful.

  Ms. Thomas explained her aspirations.

  > So I think that's where we need to do a better job and that's where we are looking and what we're working towards is getting that kind of thinking of tools that will be relevant to global students instead of just our students here.

6.6 Discussion

Thematic analysis of the interviews with MOOC producers identified three broad thematic networks. Exploring these thematic networks helped differentiate which basic themes were more prominent than others and how the thematic networks differed from each other. The following discussion considers the prominent themes from each organising theme, and compares and contrasts observations across global themes when relevant.

Global Theme 1: Diverse Conceptualisations of Inclusions was comprised of **Organising Theme 1.1: Explicit Articulation of Concern for Inclusion in the Design Process**, which had the following prominent basic theme, discussed by all six producers: **End User Concepts**. Additionally, the **Mission of University**, while not as prominent as the End User Concepts, was important and discussed by five of six producers. Global Theme 1 was also comprised of **Organising Theme 1.2: Personal and Professional Background**

Play a Significant Role, which had the following two prominent basic themes: **Work Experience, Including in Private Sector**, and **Educational Background**, both mentioned by all six producers.

Global Theme 2: Innovative Pedagogy and Program Design was comprised of **Organising Theme 2.1: Teaching and Learning Methods** and **Organising Theme 2.2: Program Design.** The basic themes within these global themes were featured with equal prominence. The interesting distinction, however, comes from the occupation-specific sorting of the organising themes. Teaching and Learning Methods was derived from comments of the Professor and Instructional Designers, whereas Program Design was derived from comments from the Program Managers. One Program Manager did contribute to both areas.

Global Theme 3: Operational Practices and Processes, Influenced by Third-space Producers was comprised of **Organising Theme 3.1: Opportunities and Constraints** and **Organising Theme 3.2: Iterative Processes**. Four of the five basic themes in this global theme were featured with equal prominence, and there was no occupational-specific sorting across organising themes.

6.6.1 Global Theme 1: Diverse Conceptualisations of Inclusion

All six producers articulated conceptualisations of inclusion as guiding their work, motivated by attention to real dimensions of disadvantage, the mission of the university, or other normative commitments from their personal and professional backgrounds. This commitment pushes the producers to implement more inclusive versions of MOOCs by conceptualising inclusion explicitly as a design principle, which Lambert (2020) found to be key in serving underrepresented learners.

The first organising theme was the explicit articulation of concern for inclusion in the design process. The most prominent theme from this organising theme was end user concepts. All six producers shared their own versions of end user concepts. All conceptualisations were of non-traditional students; for example, being a working mother or being considerably older than 24. On the one hand, the expression of concern for non-traditional learners, having an explicit conceptualisation of who that learner is and considering their needs during design, reflects a sincere commitment to inclusive design practice. Simultaneously, there are challenges that arise from having distinct perspectives across a team. The differing conceptualisations may also reflect the MOOC program evolving from an initial, more global orientation to serving ‘everybody,’ to more narrow use-cases tailored to students not admitted to the university upon first application. Regardless of the precise source of the dissonance, it existed at the time, and may pose a barrier to the effective design and construction of inclusive MOOCs.

Additionally, while many different types of inclusion were conceptualised, there was no preeminent one. Given that this thesis was predominantly written during 2020, during which protest movements for racial justice exploded across the globe and particularly in the USA in response to the murder of George Floyd (Hill et al., 2021), reflecting on the category of race as a salient feature of disadvantage is worthwhile. Race came up in the interviews, but primarily reflexively; producers noted that their own biases as white persons might inform their design process. They also noted that some of the academic achievement gaps in higher education mapped to racial lines. This never translated into explicit consideration of what racial minorities may need from a learning design perspective, however. A few reasons for this are possible. That the participants were white may reflect a biased, racialised privilege, what some scholars of race call ‘heard invisibility’ (Phillips and Lowery, 2018). Additionally, it is possible that operationalising learning design based on race is more difficult than on a variable that maps more directly to learning like not having a college degree, or a barrier to learning like caretaker responsibilities. Finally, these interviews took place in 2018, prior to the George Floyd riots; while race has always been salient in educational discussions, it is possible that only in 2020 did racial bias become a widespread phenomenon written about prolifically in the national media with broad recognition from white audiences (Beason, 2020).

One of the principles of inclusive design is to ensure that each product has clear, distinct target users; it may not be possible or appropriate to design one product to address the needs of the entire population (Inclusive Design Toolkit). The ‘fit for purpose’ model defined by King et al. (2014) takes such an approach. These insights are also important to consider given Lambert’s (2020) paper on equitable MOOCs, which highlights the capacity for inclusive designs to be achieved when specific target audiences are in mind, and this understanding is shared across a team of collaborative producers. Without a specific end user or sets of end users specified, MOOC producers run the risk of building courses that reflect traditional biases in higher education or are based on behaviour patterns and preferences of over-sampled early-adopters.

While there have been calls to adopt strategies from human factors engineering into learning analytics (Buckingham Shum et al., 2019), there may be far greater applicability of human factors concepts, like user-centred design, that could be beneficial to the MOOC discourse more broadly. Some authors have broached these subjects before, but often focused on more general concepts like usability (Xiao, Jiang, Xu, and Wang, 2014) and have yet to fully integrate learning and pedagogy into more technical considerations (Iniesto, 2017; Mendoza-Gonzalez, 2016). Merging the insights from the 'fit for purpose' MOOC with more user-centred approaches would be a valuable direction to consider, though deeper conceptualisation and theorising is needed before prompting future research.

While not as prominent as the diverse end user concepts basic theme, the Mission of the University basic theme is also worth further consideration. One of the central tensions of xMOOCs, articulated by Weller (2014) and others, is that the Silicon Valley narrative of 'broken' education needing 'disruption' failed to consider the previous four decades of distance education research. Open and distance educators and researchers invested considerable time and effort in trying to solve many of the difficulties xMOOCs encountered, especially related to democratisation. Furthermore, the production quality required to produce xMOOCs makes them prohibitively costly to make, precluding under-resourced, open-access schools charged with educating the most high-need learners. This leaves only highly selective universities with the resources capable of making MOOCs. Indeed, the most popular MOOC in 2020 was produced by Yale, hosted on Coursera (Shah, 2020). The producers' explicit mention of the mission and commitment towards inclusion of a major research university with the resources to experiment and produce MOOCs does provide a template for merging the education and technology worlds Weller describes.

The second organising theme had two prominent basic themes: professional experiences and educational experiences. All six producers mentioned professional and educational experiences as informing how they developed inclusive MOOCs. There is an old adage in politics that notes, "personnel is policy," indicating that a person's various personal, educational, professional, and other experiences that shape who they are inevitably shape how they work. This seems to be the case with the interviewees in this study, who all variously expressed the significant influence their professional and educational backgrounds had on their inclusive MOOCs practice.

The influence of working at for-profit colleges is particularly notable. The for-profit sector in higher education, perennially scorned by traditional higher education, has struggled to provide high-quality outcomes for students (Eaton, Howell, and Yannelis, 2020), and has saddled many with unsustainable debt loads (Looney and Yannelis, 2015) with a degree that has a relatively lower market value (Deming, Yuchtman, Abulafi, Goldin, and Katz, 2016). For-profits, however, do host a disproportionate share of short-term, in-demand, market-sensitive programs, invest more in their technology, and serve a disproportionately underserved demographic (Deming, 2020; Deming, Goldin, and Katz, 2012). At least two producers with a for-profit background mentioned that, while many of the outcomes and practices associated with for-profit institutions were problematic, there were important lessons to be learned about the development of high-quality technology, as well as in framing the practical value of a college degree in the labour market.

That educational experiences were prominently featured as a basic theme is more straightforward. These experiences provided producers either technical know-how or teaching and learning expertise, grounded in concepts like differentiated instruction and interactive learning. This subsequently informed how they considered inclusion during MOOC production.

6.6.2 Global Theme 2: Innovative Pedagogy and Program Design

Several specific practices articulated by the producers and embedded into course design reflect insights from adult learning theory and pedagogical best practices. The most noteworthy aspect of this global theme was the occupation-specific split between innovative pedagogy versus innovative program design. Unsurprisingly, the Professor and Instructional Designers were more focused on pedagogy, and the Program Managers were more focused on program design. This reflects what Daniel (2009) termed the division of labour of course development, with a twist. It reflects a division of labour across an entire MOOC program, with course development and design handled in one domain and program logistics, like earning credit and advancing toward a university degree, handled in another.

Regarding pedagogy, the commitment to making content relevant to real-life applications aligns with motivations for adult learners, who respond to practical, relevant information that can help improve their lives (Knowles et al., 2014). The many interactive mechanisms incorporated into course design, especially noted in the programming course, directly align with best practices for engaging pedagogy articulated by Merrill's First Principles of Instruction (2002).

That said, the observed gap between research and practice between scholars of virtual learning experiences and the practitioners building them was noteworthy. While the MOOC producers I interviewed implemented best-practice pedagogy on a number of occasions, the MOOCs, learning analytics, and online learning literatures more generally were never specifically mentioned. This also may serve as initial, provisional support for the research-praxis gap, a meso level component of hegemonic design bias.

The innovations in program design are worth discussing as well. As MOOCs have evolved to offer more formal university credit (Littlejohn and Hood, 2018), the utilisation of a series of MOOCs as an opportunity to offer an entry pathway to all students is noteworthy. Providing this sort of on-ramp to university education is innovative, unique, and reflects a commitment to inclusion and access. The prototyping of a student success centre for students enrolled in the MOOC program interested in pursuing a degree is similarly innovative. One of the largest issues facing MOOCs, especially in their ability to serve lower ability learners, is their high requirement for self-regulatory skills (Littlejohn and Hood, 2018). A student support centre based on best practices from formal online university programs, even with limited scope to serve students (potentially restricted to students indicating interest in the admission pathway), reflects a unique approach to adapt the MOOC model to support traditionally underrepresented students.

These features speak to a broader, emergent assessment of MOOCs in the literature. As King et al. (2014) note, MOOCs that are 'fit for purpose,' intentionally designed to serve a particular population toward a specific end, have demonstrated the capacity to serve underrepresented learners. This is also echoed in Lambert's (2020) assessment. Littlejohn and Hood (2018) similarly reflect on specific use-cases in which MOOCs are helping meet the needs of a specific subset of underserved learners, including refugees who otherwise might have no other access to education. These models raise the question of whether the MOOC experiment, instead of continuing a nominal commitment to serving 'everyone,' and instead of pivoting to serve already well-educated professionals looking to upskill, should instead be designed and deployed, with the corresponding program and structural supports, to meet the specific needs of underserved students. Initial evidence suggests MOOCs are already able to do this. Formally evaluating the efficacy of MOOC programs with more supportive program designs would be a fruitful area for future research.

6.6.3 Global Theme 3: Operational Practices and Processes, Influenced by Third-space Actors

Three observations regarding the third global theme are worth consideration.

First, the highly iterative nature of technology design, with multiple versions of products and constant trial and error, is paradigmatically different from the way academia approaches problem-solving. This rapid, agile development process makes it such that research insights may lose their value between the time they are observed and the time they are published. The utilisation of conference papers to help bridge this time gap is valuable and is reflective of the computer and information sciences disciplines more generally, but there continue to be considerable gaps and broader challenges between establishing a mutually beneficial, reciprocal relationship between the research and practitioner communities studying and building virtual learning experiences (Buckingham Shum et al., 2019; Ferguson et al., 2014).

Second, corporate partners and other technology partners present both opportunities and constraints. Embedding innovative technologies to improve engagement and enhance learning provides one such opportunity. With each new partner however, new technical integrations are required, and the diffuse processes inherent to building MOOCs are apt to grow larger and more complex. Furthermore, seamless data sharing and visibility into practices across all actors cannot be assumed, which presents other challenges. Specifically, the nature of and challenges in integrating learning analytics is an area in need of future research (Samuelson et al., 2019). This is difficult even when data is housed within one institution and needs to be merged. It becomes even more difficult when multiple entities need to share data to successfully integrate feedback into product and program development.

The other type of corporate partnership discussed is also noteworthy. Devising programs that can support lower- and middle-skill workers, with the investment of their employer, is a particularly interesting model to consider given the concerns raised about skills-biased technology change. These workers are the most at risk of economic dislocation resultant from automation, a trend amplified amidst the COVID-19 pandemic (Acemoglu, Autor, Hazel, Restrepo, 2020). It is also worth considering whether there are any behavioural or achievement differences between MOOC users enrolled in an employment-based program.

Finally, the prominence of third-space actors was significant, particularly the Program Managers. While other research has considered third-space actors (White and White, 2016; Hollands and Tirthali, 2014), the focus of much of the MOOC producer literature has been on Professors and Instructional Designers. The interviews in this study oversampled from a group of third-space producers presently underrepresented in the research literature, Program Managers. These Program Managers exert considerable influence on how these programs evolve and are run. Two Program Managers in my interviews were charged with helping ensure the long-run financial sustainability of the program, which ultimately affects the kinds of students the program will strive to serve. And while the Professor and Instructional Designers were aware of the need for the program to be sustainable, it was not a design constraint. Additionally, these Program Managers had considerably more knowledge and influence over the recruitment techniques used at the top of the student funnel, whereas the Professor and Instructional Designers commented that they had very little insight into those processes.

This last point raises potential implications for a meso level component of hegemonic design bias. Common user acquisition models for technology products today rely on features called ‘look-a-like’ targeting, meaning that technology producers can seek to acquire users that ‘look-a-like’ other existing users of their product. This introduces the potential for selection bias and furthers the likelihood of homophily among early-adopters (Boyd, 2010). For the host university in particular, this kind of user acquisition channel was not one of their featured strategies for the MOOC program offering, so it is generally less concerning in this use-case. Nonetheless, it did provide some insight into MOOC marketing that could help explain why MOOCs have struggled to serve underrepresented users.

6.7 Conclusions, Contributions, and Limitations

6.7.1 Conclusions and Contributions

This paper investigated the following research questions through a series of interviews with MOOC producers.

- **RQ3: What pedagogical and technology design strategies are useful to employ in attempting to build inclusive MOOCs and similar virtual learning experiences?**
    - **RQ3.1: How are MOOC producers conceptualising inclusion for the students that will use the courses they are building?**
    - **RQ3.2: What processes and practices are they engaging in toward producing inclusive MOOCs?**

Thematic analysis of the interviews uncovered several insights and contributions to the literature.

First, producers of a series of entry-level university MOOCs in the USA revealed robust, though diverse, conceptualisations of inclusion. These conceptualisations guided their practices and processes substantially, but in an ad-hoc manner. It is possible that a more explicit, consensus articulation of the particular kind of underrepresented end user a MOOC seeks to serve would be beneficial.

Second, producers employed several innovative practices toward inclusive design. They integrated interactive, engaging pedagogy, predicated on specific educational philosophies, that sought to enable diverse learners to succeed. Particularly noteworthy was the program design; the series of entry-level MOOCs provided an on-ramp to university education to anyone, including and especially to students who were originally denied admission. The concurrent prototyping of a student success centre to serve those underrepresented students is also novel. It was during the discussions of innovative practices that occupation-specific differences in focus emerged, with Professors and Instructional Designers focusing on innovative pedagogy and Program Managers focusing more on innovative programming.

The highly iterative nature of technology development, the extensive corporate partnerships, and the expansive influence of third-space actors all mark important observations for future investigations to explore, as these processes both enable and constrain inclusive MOOC development.

Work by Lambert (2020), Littlejohn and Hood (2018), and King et al. (2014) has particular relevance for this research. The specific insight from these papers is that MOOCs 'fit for purpose,' designed for an intentionally defined group of users agreed upon and understood by all producers, when coupled with student support mechanisms, provide an alternative model for MOOCs development. This alternative model could enable MOOCs to democratise learning for underrepresented students. Many of the experiments happening at the host university may provide more insight into these kinds of potential models, especially given the prototyping of a student success centre for MOOC program users, and the potential for the MOOC program to yield admission to the university.

Much of what the interviews uncovered echoed existing findings in the literature. Professors exerted considerable influence in the early stages of MOOC design (Haavind and Sistek-Chandler, 2015); MOOC producers are motivated primarily to serve a diverse audience of students and practice innovative pedagogy (Lowenthal et al., 2018; Evans and Myrick, 2015; Najafi et al., 2015); and that Instructional Designers provide ample support to teaching faculty in building MOOCs (Najafi et al., 2015). Issues of finding content under the creative commons licensing were also noted as a challenge (Lowenthal et al., 2018).

There were some notable differences as well. In contrast to findings in the extant literature (Lowenthal et al., 2018; Haavind and Sistek-Chandler, 2015), the MOOC producers interviewed in this study had ample experience in creating virtual learning experiences, primarily from building traditional online courses. Additionally, while White and White (2016) noted the strong influence of third-space actors, the findings of this study extend that insight beyond Instructional Designers to include Program Managers, who played a vital role in program development.

Finally, this study represents one of the first in-depth thematic analyses of semi-structured interviews of MOOC producers in the USA, with a particular focus on whether and how dimensions of underrepresentation are being considered during the design process. Furthermore, while not the explicit purpose of this study, observations do indicate initial, provisional support for some of the meso level components of hegemonic design bias; notably, more evidence of a gap between the MOOCs research and practitioner community (one component of research-praxis bias), as well as some potential unintended consequences of iterating models off early-adopter data, particularly in the recruitment process (early-adopter iteration bias).

6.7.2 Limitations

There were several limitations to this study that attenuated the impact of its conclusions. These include having a limited sample of six producers that was over-indexed on Program Managers. Guest et al. (2006) note that thematic saturation can be achieved with as few as six participants. Given that this study represented only one component of my thesis project, focused on a narrow range of exploratory questions, I believe thematic saturation was achieved in a local sense (rather than a global, statistically sound, or externally valid sense, as described in **Section 3.5**). Indeed, 83 codes were initially identified, which represented an exhaustive exercise; while a subjective judgement, it was determined that, having already started to note many cases where codes could be condensed, no more useful codes could be derived. Nevertheless, more data could have been enlightening. Indeed, given the small sample size, it is helpful to consider this qualitative chapter exploratory in nature and as requiring further interviews and survey data, and further analysis, to more robustly defend the results and examine if they scale. Additionally, while Program Managers are presently underrepresented in the research literature on producers, having a broader array of perspectives would have been more optimal. Less reliance on a combination of purposive and convenience sampling could have yielded better results.

The interview questions themselves may have biased the answers. Delivering this kind of an interview also requires rapport building to limit the effect of discomfort and self-editing that can take place during interviews (Seidman, 2006). In establishing rapport, I could have framed my own background in such a way that it influenced the answers. The study could have also benefited from improvements to the inter-rater reliability process; specifically, beginning this process at an earlier stage amidst the coding and initial thematic construction could have enabled more valid observations. The highly iterative nature of course development means insights likely need to be updated, though there is little evidence base, so the investigation itself was worthwhile. Additionally, conducting qualitative research is an inherently subjective process. While I tried to be as objective as possible, my own biases no doubt informed my construction of the codes, themes, and conclusions resulting from this work.

7 TOWARD MORE INCLUSIVE MOOC DESIGN: PRIMARY CONCLUSIONS AND LIMITATIONS, AREAS FOR FUTURE RESEARCH, AND PRACTICE AND POLICY APPLICATIONS

The end of this science [ethics] is not knowledge but action.
– Aristotle

7.1 Chapter Overview

This chapter attempts to bring this thesis to conclusion. **Section 7.2** considers the primary conclusions and contributions of this thesis to the MOOCs research literature, as well as limitations and areas for future research. **Section 7.3** considers how to apply some of the insights to practice and policy, with a particular focus on economic development policy in the context of skills-biased technology change. **Section 7.4** concludes with closing comments.

7.2 Summary of Conclusion and Implications for Research

Chapters 1-3 described why and how this thesis pursued a multimethod (Hunter and Brewer, 2015), post-positivist (Phillips, 1990), subtle realist (Hammersley, 1992) research design aimed at contributing to the MOOC literature across conceptual, quantitative, and qualitative domains. These descriptions explored the tensions and contradictions of MOOCs as a potential mechanism to democratise learning for underrepresented groups (Littlejohn and Hood, 2018), particularly adults without college degrees and those from lower socioeconomic backgrounds in the USA, who face the greatest risks of economic vulnerability resultant from skills-biased technology change (Autor and Reynolds, 2020; Barrero et al., 2020).

Chapter 4 engaged in theory-building research (Kettley, 2010), developing a new conceptual framework, hegemonic design bias. This framework contributes an ecosystem-wide set of operationalisable hypotheses to account for MOOCs struggling to democratise learning. This was pursued, in part, because of the lack of reciprocal engagement between theory and empirical work in the nascent MOOC literature (Bozkurt et al., 2017). Hegemonic design bias describes a series of biases and constraints at the macro, meso, and micro levels of the distance education ecosystem that impair institutions of higher education in the provision of inclusive MOOCs. At the macro level, these constraints are manifest in the higher relative value on knowledge production over knowledge dissemination, exclusionary admissions procedures, and institutional isomorphism, which combine to incapacitate elite higher education from providing teaching and learning to diverse populations. At the meso level, homophily among early-adopting MOOC users, particularly in that they are disproportionately highly educated, has potentially biased learning analytics to make recommendations for how to optimise course design for already-advantaged learners. This may lead to research-praxis bias, in which practitioners use analysis biased toward well-educated learners to improve course design. It is unclear the extent to which MOOC producers themselves are even that connected to the learning analytics and research community, so while the potential bias of learning analytics itself may be avoided, this underscores the risk of a broader disconnect between the research and practitioner community that is sub-optimal. Finally, at the micro level of course design, a series of design choices reflective of behaviourist pedagogy, a lack of scaffolding, a requirement of high levels of self-regulation and high levels of digital literacy, all potentially make MOOCs an unwelcome and challenging environment for learners without tertiary education. Similarly, the sophisticated content, both in terms of actual information presented, and in terms of English fluency required to engage, do not consider the reality of non-tertiary educated Americans, many of whom struggle with literacy, numeracy, and English fluency.

Hegemonic design bias remains a conjecture. While broad evidence was marshalled to support its claims, the next phase of theory-building requires the framework to be formally tested (Kettley, 2010). My own future research will continue down this path. My hope is that other researchers might find some of its hypotheses compelling or in need of additional clarification, so they can utilise hegemonic design bias to investigate MOOCs. This could be conducted at the macro, meso, and micro levels of the framework separately, in piecemeal fashion, or all at once. Additionally, more research is needed in the field based on the premises which led to hegemonic design bias; that is, clearer and more focused explorations and examinations of why MOOCs have struggled to democratise learning.

Chapter 5 explored engagement and achievement patterns of traditionally underrepresented learners in entry-level MOOCs, inspired by the extant literature consensus that clusters of learner groups are commonly observed in MOOC data (Li and Baker, 2018) but with little insight into whether those subgroups are differentiated by demographic variables (Gardner and Brooks, 2018; Deng et al. 2017) like education background and SES. Analysis of an initial data set of some 260,000 learners, narrowed to a subset of about 29,000 committed learners, revealed that the common clusters of subgroups found in the existing MOOC literature are indeed observed in entry-level MOOCs. Traditionally underrepresented learners on the dimension of education level, however, are more likely to sort into the commonly observed successful subgroups of learners compared to their better-educated peers. Simultaneously, these learners are also more likely to sort into sampling and auditing subgroups that demonstrate engagement but eventually stop out, potentially indicating a need to experiment with more supports for these learners. Additionally, utilising a categorical variable like education level as a feature to derive clusters, utilising a distance measure like Gower (Ebbert and Dutke, 2020; Gower, 1971), may be a worthwhile approach to consider, as it allows researchers to focus more narrowly on the engagement and achievement patterns of traditionally underrepresented learners.

The cluster analysis was limited in important ways. It lacked detailed feature data that could unveil deeper insights into learner behaviour. In the future, a more careful and intentional selection of feature data, applied to similar analysis focused on demographic heterogeneity within clusters, could advance this work. Additionally, pairing this more feature-sensitive analysis with richer survey data on the motivations of these learners would be valuable.

Chapter 6 explored thematic analysis of qualitative interviews to better understand the MOOC producer perspective, an under-researched area of the literature (Zhu et al., 2018a; Veletsianos and Shepherdson, 2016; Gašević et al., 2014), particularly in whether and how MOOC producers consider underrepresented groups in their design processes. Several insights were revealed. The interviewees, producers of entry-level university MOOCs, described robust, diverse conceptualisations of inclusion as guiding their design processes. The commitment was sincere, though ad-hoc and not always consistent. These commitments did guide their practices and processes substantially. In particular, the producers integrated interactive, engaging pedagogy, predicated on specific philosophies of learning, that sought to enable diverse learners to succeed. Additionally, sound pedagogy was paired with innovative program design; the series of entry-level MOOCs provided an on-ramp to university education to anyone, including students that were originally denied admission to a traditional university program. The concurrent prototyping of a student success centre to serve underrepresented students is notable for the MOOC context. The highly iterative nature of technology development, the diverse array of corporate partners, and the expansive influence of third-space actors, all mark important observations for future investigations to explore, as these are processes that both enable and constrain inclusive MOOC development. Finally, the gap between research and practice, noted in the learning analytics literature (Buckingham Shum et al., 2019; Ferguson and Clow, 2017) and a core component of the meso level of hegemonic design bias, was observed. Closing the learning analytics loop and establishing more reciprocal and mutually beneficial processes between the research community and practitioner community is needed. These interviews were limited by the sample size; more data from a broader set of producers will be beneficial for future iterations of this kind of work.

Immediate next steps for my research program were clarified. An unexpected outcome of **Chapter 2** was considerable engagement with the philosophy of science literature, and what those debates can bring to bear on MOOC questions. I intend to pursue these avenues of inquiry. It will be beneficial to train more specifically in bibliographic research methods to complete a more rigorous, formal review of the MOOC literature through a philosophy of science lens.

Regarding hegemonic design bias, and future endeavours into learning analytics and qualitative work, I intend to more robustly operationalise and test the components of hegemonic design bias. Specifically, I will pursue similar cluster analysis explorations with richer feature data to investigate whether types of engagement, such as discussion forum participation, are heterogenous across subgroups along demographic dimensions. I would like to engage with experimental pedagogical interventions to measure whether certain treatments have differential impacts on subgroups of learners. In terms of qualitative work, I would like to continue to explore the producer perspectives. One insight that emerged from the interviews as well as in developing hegemonic design bias was that questions of user acquisition of learners are vital to MOOCs, and not particularly well-understood. User acquisition strategies are likely a core dynamic leading to the disproportionate enrolment of highly educated users in MOOCs. Developing deeper insights into these dynamics is essential moving forward.

Finally, I hope to engage more broadly with the workforce development literature. Forthcoming research with colleagues from Facebook Research (Laguna-Muggenberg, Bhole, and Meaney, 2021) provides insight into the relative likelihood of different demographics to upskill formally through courses or informally through on the job training. In the context of skills-biased technology change, these insights will be valuable to developing policies that better enable elementary- and middle-skill workers to successfully transition in the labour market.

7.3 Broader Research Implications, and Practice and Policy Applications

Beyond the specific contributions of the chapters and my own plans for taking this research forward, there are a few broader points to consider regarding research, practice, and policy.

While hegemonic design bias was developed concurrent to the execution of my qualitative and quantitative chapters, some provisional evidence emerged supporting hegemonic design bias that will contour future investigations. First, the cluster analysis presented in **Chapter 5**, while heavily subsetted and beset by other methodological limitations common to learning analytics (Gardner and Brooks, 2018), does lend support to the notion that disaggregating data can help reveal heterogenous engagement patterns along demographic lines. More investigations utilising these analytic methods could yield important insight into specific course design choices that either enable or constrain subgroups of learners. Secondly, more research into the top of the MOOC funnel is needed, and specifically, why highly educated students are so overrepresented. That even entry-level MOOCs remain disproportionately concentrated with highly educated users is worthy of future investigation.

Regarding practice, **Chapter 6** provides some evidence that the second feature of research-praxis bias, that practitioners do not benefit from the advances from the research community, is at least present among the university producers I interviewed. More work is needed to understand this dynamic and to close this gap. The conclusion of **Chapter 4** on hegemonic design bias set out some hypotheses for how this could be operationalised, for example, implementing a series of professional development interventions for MOOC producers that provided insight into cutting edge research and devising innovative ways to test the efficacy of this.

Another possibility of closing the research-praxis gap could involve utilising learning analytics in practice-oriented ways. For example, one productive outcome of the labelling strategy pursued in **Chapter 5** to develop the cluster analysis was the creation of learning analytic dashboards at the host university. These dashboards enable Professors, Instructional Designers, and Program Managers to observe students over course epochs and to identify areas when students move from on-track to off-track. With these dashboards, more targeted interventions can be directed to noted areas of attrition. An example of these dashboards is illustrated in **Figure 7.1**

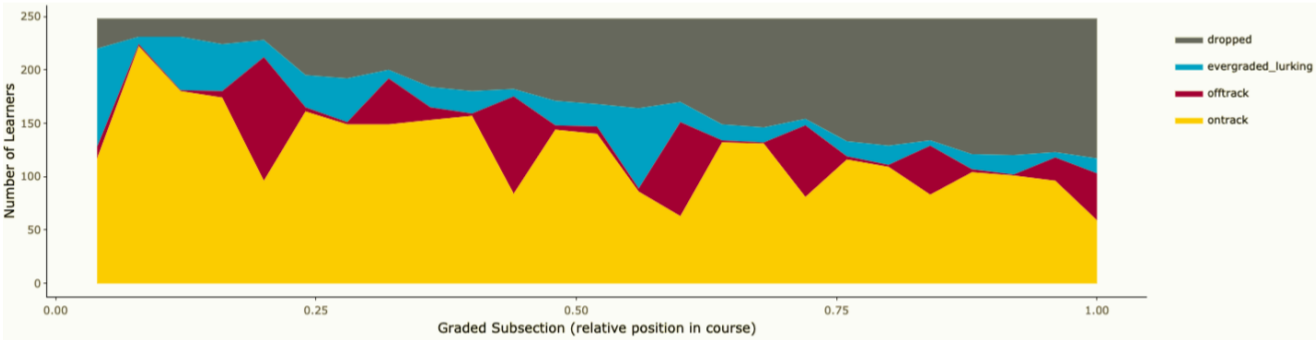


Figure 7.1 Learning analytic dashboards designed based on the data labelling utilised in cluster analysis, illustrating funnels of participation for students across a range of outcomes.

Several important policy considerations emerged from this thesis as well. While only commented on briefly here, these will continue to guide my future research and can hopefully stimulate similar research in the field.

Situating the development of MOOCs in the context of skills-biased technology change is important. It underscores the extent to which accelerating returns to more cognitively intense, non-routine skills, concurrent to polarised job growth in the labour market (Autor, 2019; Autor, 2014), is worsening levels of already historic inequality. The COVID-19 pandemic amplified these trends (Autor and Reynolds, 2020) with estimates that upwards of 40 percent of job losses, disproportionately experienced in elementary and middle-skill occupations, will be permanent (Barrero et al., 2020). These trends exist alongside inadequate learning and training infrastructure for adults. Existing workforce programs are riddled with barriers to entry and selection biases, inefficiencies, and varying levels of quality within and between states, paired with a tapestry of funding sources and confusing bureaucratic processes to gain access (Escobari et al., 2019). Furthermore, the design of these programs regularly neglects to consider the entire user journey required to make difficult workforce transitions. Policies are needed that consider the end-to-end user journey, illustrated in **Figure 7.2**, and that enable non-tertiary educated adults to engage successfully with lifelong learning and training.

Figure 7.2: **The end-to-end user journey of a workforce transition. From Escobari, Seyal, and Meaney, 2019.**

One feature of this user journey that requires intentional support from the public and social sector is providing good content and good teaching. As we see in the case of MOOCs, particularly at the micro level of hegemonic design bias, several pedagogical and technology design flaws prevent these kinds of courses from reaching learners who would most benefit. To that end, establishing policies and resources that incentivise the intentional design and development of educational technologies that enable specified groups of underrepresented learners to successfully engage in lifelong learning could prove useful.

One set of policies recently articulated by researchers in conjunction with the Brookings Institution provides a framework for doing so. Richard Arun and Mitchel Stevens (2020) call for Learning Opportunity Credits (LOCs) to be made available to all unemployed adults and adults who receive the Earned Income Tax Credit. LOCs are aimed at promoting workforce training and stimulating the expansion and development of high-quality, flexible models of adult learning for labour market advancement. Arun and Stevens (2020) pair LOCs with a call for the federal government to establish a national project on the Future of Learning, Opportunity, and Work (FLOW). The goal of FLOW would be to accumulate knowledge on best practices for adult learning and inform policy (Arun and Stevens, 2020).

I would augment FLOW to include specific grants funded by the Department of Education or the Department of Labour, structured similarly to National Institute of Health or National Science Foundation grants, to enable medium- and longer-term experimentation that explicitly incentivise the development of educational technologies for adults without a college degree. This could be paired with more resources from the social and private sectors. These grants would be inspired by the small but important literature on MOOCs that demonstrates specific, 'alternative' (Lambert, 2020), 'fit for purpose' (King et al., 2014) MOOCs are designed in creative ways that enable underrepresented learners to succeed in them. Specifically, building off the operationalisation of hegemonic design bias, these grants should stipulate that funding for the development of these courses be tied to:

- A clear articulation of a target user; specifically, adults without a college degree
- Adult learning theory informed-pedagogy, that prioritises:
    - Interactive content and engagement among learners
    - Scaffolded content that accommodates the broad range of adult literacy and numeracy in the population, based on available evidence and data
    - Interventions that support the development of self-regulated learning strategies
- User experience design accounting for broad ranges of digital literacy among diverse, non-college-educated adult populations
- Content, including remedial content, reflective of the learning needs of adults transitioning in the workforce
- Access for non-English fluent speakers
- Disaggregated business analytic and research approaches that explore potentially heterogenous patterns of enrolment, engagement, and achievement among diverse learners.

Supporting technology design and development with funding tied to these specific constraints could begin to work against the existing tendencies toward hegemonic design bias in the development of tertiary virtual learning experience.

7.4 Concluding Comments

In the *Battle for Open*, Martin Weller (2014) laments the Silicon Valley narrative of 'disrupting' education through MOOCs, in part because MOOCs ignored the previous four decades of research on open and distance learning. Researchers and practitioners in the field have long been aware of the unique challenges adult learners face. There are no easy solutions to these challenges, and technology alone cannot ameliorate them (Reich, 2020).

At the same time, MOOCs and similar virtual learning experiences represent an unprecedented opportunity for distance learning, especially as the learning analytics community continues to develop new methodologies for working with massive amounts of data that enable granular insights into teaching and learning. What is required now is a concerted effort to align the goals that these efforts are channelled toward, among researchers and practitioners. If the goal of MOOCs remains to democratise education, especially for those who do not have a tertiary degree, to be a force for improved economic opportunity through more inclusive learning, this needs to be explicitly stated, incentivised, and vigorously pursued.

Appendices

Appendix 3.1: Cambridge Ethics Approval

RESEARCH ETHICS REVIEW CHECKLIST FOR FACULTY OF EDUCATION

The Faculty's Three Stages of Ethical Clearance

Stage 1 involves you in completion of this Ethics Review Checklist. This is the first stage of three. It will help you (and others) decide to what extent you need to become involved in the second and third stages. When you have completed it you (and the Faculty) will be in a position to make this judgement.

Stage 2 will involve you in discussing any ethical dimensions of your research in some depth with your another 'knowledgeable person of standing'; this is a very likely outcome of completing the checklist. Further details are provided in Section C.

Stage 3 will involve you in obtaining formal 'ethical clearance' through the Faculty of Education's procedures; some projects will need to proceed to this stage. Further details are provided in Section C .

Most of the questions on this checklist deliberately offer you just two answers ('yes' or 'no'). You will probably find that you can answer many of the questions unequivocally one way or the other. However, sometimes you may wish there was an 'it depends' response category. If you find yourself in this position, please give the answer which suggests that, at this preliminary stage, there might be an ethical issue requiring more discussion at Stage 2.

RESEARCH ETHICS REVIEW CHECKLIST FOR FACULTY OF EDUCATION

Section A: Details of the Project

Student Name	Mike Meaney
Email	Mjm234@cam.ac.uk
Supervisor	[redacted]
Supervisor email	[redacted]
Registration Report Title	Massive Open Online Courses and the Future of Educational Inequity

Section B: Checklist

Code of Practice relating to Educational Research		
1a	Have you read the *Revised Ethical Guidelines for Educational Research* (2011) of the British Educational Research Association (BERA)? (if you have not read it, the latest version is available at http://www.bera.ac.uk/researchers-resources/publications/bera-ethical-guidelines-for-educational-research-2011	**Yes**/No
1b	Is this Code relevant to the conduct of your research? If you have answered 'no', please briefly explain why:	**Yes**/No
1c	Do you agree to subscribe to the Code in carrying out your own research?	**Yes**/No
2	Are there any aspects of your proposed research which, in the context of BERA's Code of Practice, might give rise to concern amongst other educational researchers?	Yes/**No**
If you have answered 'yes', please briefly list possible causes for concern below:		
a		
b		
c		
3a	Will you be analysing an existing data set that has already been collected by someone else?	Yes/**No**

3b	If you answered YES: can you confirm that the data you will be using is *either* Already available in the public domain for anyone to analyse Or You have been given permission by the owner of the data set to undertake your own analysis and results[1]	Yes/No
4	Will you be collecting your own research data for the study (through such techniques as interviewing people, observing situations, issuing questionnaires etc)? ***nb. If you have answered NO to this question, you may proceed to Section C and need not answer any further questions in this section.***	**Yes**/No
Obtaining 'Informed Consent'		
5	Are you familiar with the concept of 'informed consent'? (if you are not familiar with this concept you should first consult the following source: page 5 of the BERA guidelines above).	**Yes**/No
6	Does your research involve securing participation from children, young people or adults where the concept of 'informed consent' might apply? *Permission is likely to be needed to report any information about people or institutions that is not in the public domain, and which you have been able to obtain due to your privileged access to the research site(s) in whatever capacity* [2]	Yes/**No**
If you have answered 'yes' to Question 6 above, please answer the following questions.		
7a	Do you believe that you are adopting suitable safeguards with respect to obtaining 'informed consent' from participants in your research in line with the Code of Practice?	Yes/No
7b	Will all the information about individuals and institutions be treated on an 'in confidence' basis at all stages of your research including writing up and publication?	Yes/No

[1] *this permission should only be given if the owner of the data can make it available for secondary analysis on the basis of the informed consent they obtained from their original participants*

[2] *Professional work (such as teaching) can involve the collection of evidence to better understand problems/issues and to evaluate innovative practice - leaving practitioners with the question of when these activities become formal research requiring informed consent. This comment is meant to highlight how the collection of data for public reporting **beyond the institution** (e.g. **in a thesis**) should be considered as a key criterion for deciding when informed consent is required.*

7c(i)	Will all the information collected about the institution(s) where research is based be presented in ways that guarantee the institution(s) cannot be identified from information provided in the report? *Note: in a thesis written by a researcher about a research context where they have a publicly acknowledged role, it is difficult to disguise the identity of the institution whilst also providing the expected detail of the researcher's relationship with the research context.*[3]	**Yes**/No
7c(ii)	If not, has the appropriate responsible person given approval for the research on the understanding that the identity of the institution cannot be protected in the report of the research?	Yes/No
7c(iii)	Will all the information collected about individuals be presented in ways that guarantee their anonymity? *Note: a person with a named role, or having a specific set of reported characteristics that is unique in the research context, cannot be assured of the anonymity when the identity of the research site cannot be protected.*	**Yes**/No
7c(iv)	If not, have these issues been explained to the relevant participants (and appropriate gatekeepers in the case of children or other vulnerable participants)?	Yes/No
The Involvement of Adults in the Research		
8a	Will your research involve adults?	**Yes**/No
If you have answered 'yes' to Question 8a above, please answer the following questions; otherwise move to Question 9.		
8b	Will these adults be provided with sufficient information *prior* to agreeing to participate in your research to enable them to exercise 'informed consent'?	**Yes**/No
8c	Will the adults involved in your research be in a position to give 'informed consent' themselves with respect to their participation?	**Yes**/No

[3] *At present the implicit assumption is that anonymity is always desirable*, and is always achievable. In many studies these assumptions are sound. However, a practitioner (e.g. teacher) reporting research into their own practice/institution in a thesis would normally need to be explicit about their professional relationship to the research context to give an authentic account of their research. As the staff lists of many educational institutions are in the public domain and often readily found by a web search, a thesis by a named member of staff allows the institution to be readily identified from the name of the thesis author.*
Given that an institution can readily be identified, this also has consequences for the degree of anonymity that can be promised to participants - for example those with named roles such as Head of Year 11, Student Voice Coordinator, Head Prefect, etc, or those identifiable from detailed reported characteristics.
** Some institutions or participants may welcome being acknowledged by name in a thesis, and their views should be taken into account and balanced against other considerations.*

8d	Will these adults be able to opt out of your research in its entirety if they wish to do so by, for example, declining to be interviewed or refusing to answer a questionnaire?	**Yes**/No
8e	Will these adults be able to opt out of parts of your research by, for example, declining to participate in certain activities or answer particular questions?	**Yes**/No
The Involvement of Children, Young People and other potentially Vulnerable Persons in the Research		
9a	Will your research involve children, young people or other potentially vulnerable persons (such as those with learning disabilities or your own students).	Yes/**No**
If you have answered 'yes' to Question 9a above, please answer the following questions; otherwise move to Question 10. In educational and social research 'informed consent' regarding access is often given by a 'gatekeeper' on behalf of a wider group of persons (e.g. a head or class teacher with respect to their pupils, a youth worker working with young people, another person in an 'authority' position).		
9b	Who will act as the 'gatekeeper(s)' in your research? Please list their position(s) briefly below and, where this is not self-evident, describe the nature of their relationship with those on whose behalves they are giving 'informed consent'. **The researcher cannot act as the gatekeeper (see 9g below)**	
i		
ii		
iii		
9c	Will you be briefing your 'gatekeeper(s)' about the nature of the questions or activities you will be undertaking with the children, young people or other potentially vulnerable persons involved in your research?	Yes/No
9d	If another person (such as a teacher or parent of a child in your study) expressed concerns about any of the questions or activities involved in your research, would your 'gatekeeper(s)' have sufficient information to provide a brief justification for having given 'informed consent'?	Yes/No
9e	If unforeseen problems were to arise during the course of the research, would your 'gatekeeper(s)' be able to contact you at relatively short notice to seek advice, if they needed to do so?	Yes/No
9f	Could your 'gatekeeper(s)' withdraw consent during the research if, for whatever reason, they felt this to be necessary?	Yes/No
9g(i)	Are you undertaking research into your own professional context/institution (e.g. with students in a school where you work)? If you answered 'Yes' then you should identify (in 9b above) a suitable senior person who has agreed to act as an independent point of contact for participants to act as the gatekeeper, and answer the following two questions:	Yes/No

9g(ii)	Will you ensure that other people in the research context are aware of the identity of the gatekeeper?	Yes/No
9g(iii)	Will you take reasonable precautions to ensure that research participants (and where appropriate their parents/guardians) know that they should contact the gatekeeper (and not you) if they have any concerns about the research?	Yes/No
Other Ethical Aspects of the Research		
10	Will it be necessary for participants to take part in the study without their knowledge and consent at the time? (eg covert observation of people in public places)	Yes/**No**
11	Will the research involve the discussion of topics which some people may deem to be 'sensitive'? (e.g. sexual activity, drug use, certain matters relating to political attitudes or religious beliefs)	Yes/**No**
12	Does the research involve any questions or activities which might be considered inappropriate in an educational setting?	Yes/**No**
13	Are drugs, placebos or other substances (e.g. food substances, vitamins) to be administered to study participants or will the study involve invasive, intrusive or potentially harmful procedures of any kind? *If you have ticked 'Yes' it is vital to refer the matter to the Faculty Research Office for onward reference to the University Insurance Section.*	Yes/**No**
14	Will blood, tissue or other samples be taken from the bodies of participants?	Yes/**No**
15	Is pain or more than mild discomfort likely to result from the study?	Yes/**No**
16	Could the research involve psychological stress or anxiety or cause harm or negative consequences beyond the risks encountered in normal life?	Yes/**No**
17	Are there any other aspects of the research which could be interpreted as infringing the norms and expectations of behaviour prevailing in educational settings?	Yes/**No**
18	Are there any other aspects of the research which could be to the participants' detriment?	Yes/**No**
19	Will the study involve prolonged or repetitive testing?	Yes/**No**
20	Will financial inducements (other than reasonable expenses or compensation for time) be offered to participants?	Yes/**No**

SECTION C: Interpretation of Results

If any of your answers coincide with the response options having a coloured background, then you should assume that further discussion involving Stage 2 procedures is required because some aspect of your proposed research is likely to be 'ethically sensitive'. In practice, many issues can be resolved at this stage. In practice, many issues can be resolved at this stage.

Members of staff should be especially careful about research involving their own students (question 9g).

If you have ticked 'yes' in response to one or more of questions 10 to 20, both Stage 2 ***and*** *Stage 3 clearance will definitely be required.*

Stage 2 Clearance
Any 'ethically sensitive' responses identified above should be discussed with a 'knowledgeable person of standing'. In the case of students within the Faculty, this person will, in almost every case, be the person supervising your research.

On completion of the discussion, the 'knowledgeable person of standing' is asked to choose one of the following three responses, to delete the other two and to affirm their views by adding their signature.	
A	I have discussed the ethical dimensions of this research and, as outlined to me, I do not foresee any ethical issues arising which require further clearance.

Supervisor Name/ Signature	[redacted]
Date	26-6-17

Appendix 3.2: Host University Internal Review Board Approval

SOCIAL BEHAVIORAL INSTRUCTIONS AND TEMPLATE		
NUMBER	DATE	PAGE
HRP-503a	10/30/17	1 of 6

Instructions and Notes:

- Depending on the nature of what you are doing, some sections may not be applicable to your research. If so, mark as "NA".
- When you write a protocol, keep an electronic copy. You will need a copy if it is necessary to make changes.

1 Protocol Title

Include the full protocol title: MOOCs and Educational Equity: For whom are MOOCs working, and how?

2 Background and Objectives

Provide the scientific or scholarly background for, rationale for, and significance of the research based on the existing literature and how will it add to existing knowledge.

- Describe the purpose of the study.
- Describe any relevant preliminary data or case studies.
- Describe any past studies that are in conjunction to this study.

I am interested in leveraging learning analytics on massive data sets of user behaviour for traditionally underrepresented learners on [redacted]. First, I seek to deploy a survey that measures demographic variables and learner motivations. Using regression analysis, I seek to determine: whether demographic variables are predictive of MOOC completion and how motivation affects performance for traditionally underrepresented students. Using machine learning methods, I seek to determine: what the "funnel of engagement" looks like for traditionally underrepresented users (based on Clow 2013) and what do patterns of interaction and engagement (click streams: video logs, page view logs, discussion forum logs) look like for traditionally underrepresented users (based on Kizilcec 2015). I will pair these quantitative findings with qualitative interviews of traditionally underrepresented MOOC users to gain a more granular sense of their user experience. Finally, I will interview professors, instructional designers, and developers, about the design processes they employ when creating MOOCs, through the lens of value-centric design thinking. I situate this work in a broader framework concerning the nature of technological progress and innovation, and how to make those processes more equitable and sustainable.

There exist several gaps in the existing MOOCs literature that my analysis seeks to fill. Beyond a few papers (Dillahunt 2014; Zhenghao 2015; and Stich and Reeves 2017), there has been little to no specific focus on understanding the motivation factors and behaviour patterns for traditionally underrepresented students.

The purpose of this IRB document is to set out the scope of the study taking place between January 2018 – December 2018, as well as the pilot version of this study carried out during July 2017 – September 2017.

My proposal will also be vetted through the University of Cambridge IRB, and has already received initial approval.

3 Data Use

Describe how the data will be used. Examples include:

- Dissertation, Thesis, Undergraduate honors project
- Publication/journal article, conferences/presentations
- Results released to agency or organization
- Results released to participants/parents
- Results released to employer or school
- Other (describe)

This data will be used for publication of journal articles and a PhD thesis at the University of Cambridge.

4 Inclusion and Exclusion Criteria

Describe the criteria that define who will be included or excluded in your final study sample. If you are conducting data analysis only describe what is included in the dataset you propose to use.

Indicate specifically whether you will target or exclude each of the following special populations:

- Minors (individuals who are under the age of 18)
- Adults who are unable to consent
- Pregnant women
- Prisoners
- Native Americans
- Undocumented individuals

The data from all enrolees the [redacted] accessing the course through the edX MOOC platform between the dates of Jan 1, 2017 and June 1, 2017 will be used in this study. Of all the participants in the course (50,000), 3% specified in a survey that they were under age 18. A significant portion (14%) did not specify their age.

5 Number of Participants

Indicate the total number of participants to be recruited and enrolled for the quantitative component of the study*:* 50,000 contacted; we expect a ten percent return rate

Indicate the total number of participants to be recruited and enrolled for the quantitative component of the study*:* 25 interviewees

6 Recruitment Methods

- Describe who will be doing the recruitment of participants.
- Describe when, where, and how potential participants will be identified and recruited.
- Describe and attach materials that will be used to recruit participants (attach documents or recruitment script with the application).

The data used in this study will be retrospective. Participants enrol in the course through the MOOC platform, edX. Students who enrol with edX must sign the edX Terms of Service Agreement and Privacy Policy. These agreements allow for participant data to be used by educational institutions that own the content of the course for research purposes.

Survey data will be collected from students who choose to take an optional survey before the course begins. Screenshots of this survey can be found in appendix A. Students will not be “recruited” to take the survey. It is fully optional. There is no additional consent form provided along with the survey. Consent for this survey is covered by the standard edX Terms of Service Agreement and Privacy Policy.

An additional survey question to be inserted will ask whether individuals taking the course will be willing to participate in follow up interviews. From this pool, users will be selected for the qualitative interviews.

All participants selected for interviews will first sign an additional research consent form. This additional consent form has been developed from HRP-502a – TEMPLATE CONSENT SOCIAL BEHAVIORAL template document. (See the attached form labelled: Meaney student_interview CONSENT DOCUMENT and Meaney producer_interview CONSENT DOCUMENT)

7 Procedures Involved

Describe all research procedures being performed, who will facilitate the procedures, and when they will be performed. Describe procedures including:

- The duration of time participants will spend in each research activity.
- The period or span of time for the collection of data, and any long term follow up.
- Surveys or questionnaires that will be administered (Attach all surveys, interview questions, scripts, data collection forms, and instructions for participants to the online application).
- Interventions and sessions (Attach supplemental materials to the online application).
- Lab procedures and tests and related instructions to participants.
- Video or audio recordings of participants.
- Previously collected data sets that that will be analysed and identify the data source (Attach data use agreement(s) to the online application).

*A full explanation of the methodology for this study can be found in the attached document, Meaney_research methods and pilot_8.21.17. This document covers both the full research project as well as the proposed pilot.

Computer data generated by participants in the [redacted] course will analysed. This data will include:

- Course skill worked on
- Number of attempts on particular problems
- Whether the attempt was successful or unsuccessful
- Whether the student asked for a hint
- Other available click-stream data from edX

This data will be combined with daily activity log data that includes:

- How long the participant was logged into the course on a particular day
- How far the participant has progressed through the math course
- What course skills the participant has mastered as of a particular date
- What course skills the participant worked on a particular date
- What course skills are in the participant's que to work next

Both of these data sets will be combined with general demographic data obtained from a short survey given by edX at the beginning of each course. This demographic data includes:

- Participant's age
- Participant's gender
- Participant's highest level of education achieved
- Participant's parents highest level of education achieved
- Participant's country
- Participant's racial/ethnic background
- Participant's motivations for taking the course
- Whether or not the participant opted for ID verification so they can prove that they themselves took the final in the course (The photos used for ID verification will not be used or be part of the study only the information that the participant opted for ID verification.)

Machine learning techniques such as cluster analysis and random forest classification will be used to analyse this data as well as prediction methods such as multiple linear and logistic regression.

For the qualitative analysis, student users will be asked to reflect on the following questions:

Prompt 1: Please tell me a little bit about yourself.

- Can you tell me a bit about your family?
- What do you do?
- How was your experience in school growing up?

Prompt 2: Please tell me a little bit about why you decided to take this MOOC.

- Why did you decide to try to take this MOOC?
- How did you hear about it?
- What were your goals in taking it?

Prompt 3: How was your experience?

- What did you like?
- What did you not like?

Prompt 4: Please tell me about how you tried to work on the MOOC.

- Were you on your phone, laptop, or a desktop?
- What time of day was it?
- What constraints did you face in completing the MOOC?

Prompt 5: Please tell me a bit about how the MOOC could have been made better.

Additionally, individual student log data will be available for discussion in the interview.

For the qualitative analysis, professors, instructional designers, and program managers of the [redacted] program will be asked to reflect on the following questions:

Prompt 1: How did you become involved in making MOOCs?
- Were you excited by this prospect?
- Did you have much experience with technology previously?

Prompt 2: When making your MOOC, who do you envision as the end user?
- Is this different or similar to your standard student?
- Do you consider that MOOCs might be used by traditionally underrepresented users?
- Do you consider "equity" as a design constraint?

Prompt 3: What learning and pedagogy theory do you reference when making MOOCs?

Prompt 4: Do you focus on engagement and motivation during the design process? If so, how?
- Does SDT come to mind at all into the design process?

Prompt 5: What are you most proud of regarding the MOOCs?
- Has the working on the MOOC been an overall positive or negative experience?

Prompt 6: What would you like to see improved with MOOCs?

8 Compensation or Credit

- **Describe the amount and timing of any compensation or credit to participants.**
- **Identify the source of the funds to compensate participants**
- **Justify that the amount given to participants is reasonable.**
- **If participants are receiving course credit for participating in research, alternative assignments need to be put in place to avoid coercion.**

No compensation will be offered to participants of this study.

9 Risk to Participants

List the reasonably foreseeable risks, discomforts, or inconveniences related to participation in the research. Consider physical, psychological, social, legal, and economic risks.

There are no foreseeable risks, discomforts, or inconveniences related to participation in this research.

10 Potential Benefits to Participants

Realistically describe the potential benefits that individual participants may experience from taking part in the research. Indicate if there is no direct benefit. Do **not** include benefits to society or others.

It is possible that completion of this survey or participation in interviews may lead to increased engagement in the course or online learning in the future.

11 Privacy and Confidentiality

Describe the steps that will be taken to protect subjects' privacy interests. "Privacy interest" refers to a person's desire to place limits on with whom they interact or to whom they provide personal information. Click here for additional guidance on [redacted]

Describe the following measures to ensure the confidentiality of data:

- Who will have access to the data?
- Where and how data will be stored ([redacted].)?
- How long the data will be stored?
- Describe the steps that will be taken to secure the data during storage, use, and transmission. (e.g., training, authorization of access, password protection, encryption, physical controls, certificates of confidentiality, and separation of identifiers and data, etc.).
- If applicable, how will audio or video recordings will be managed and secured. Add the duration of time these recordings will be kept.
- If applicable, how will the consent, assent, and/or parental permission forms be secured. These forms should separate from the rest of the study data. Add the duration of time these forms will be kept.
- If applicable, describe how data will be linked or tracked (e.g. masterlist, contact list, reproducible participant ID, randomized ID, etc.).

If your study has previously collected data sets, describe who will be responsible for data security and monitoring.

[redacted] and Mike Meaney will have access to these data and will be responsible for data security, monitoring, and access.
Data will be stored on [redacted] storage media, including: [redacted] Google Drive cloud storage, [redacted] dropbox, secure [redacted] servers (ITFS 1). All of these can only be accessed with [redacted] credentials.
The data will be stored from the time of IRB approval until May 1, 2019.
The data will not be shared with anyone else who does not separate authorization to access and see this data.
Data will be de-identified. All information that could be used to identify individual users will be removed and replaced with an anonymous id.

Users selected for interviews will be linked to their demographic, survey, and user activity. This information may be referenced during the interview. An anonymous data key will be used to link the survey information to the user activity information, likely [redacted] student id number.

12 Consent Process

Describe the process and procedures process you will use to obtain consent. Include a description of:

- Who will be responsible for consenting participants?
- Where will the consent process take place?
- How will consent be obtained?
- If participants who do not speak English will be enrolled, describe the process to ensure that the oral and/or written information provided to those participants will be in that language. Indicate the language that will be used by those obtaining consent. Translated consent forms should be submitted after the English is approved.

The data used in this study will be retrospective. Participants enrol in the course through the MOOC platform, edX. Students who enrol with edX must sign the edX Terms of Service Agreement and Privacy Policy. These agreements allow for participant data to be used by educational institutions that own the content of the course for research purposes.

Survey data will be collected from students who choose to take an optional survey before the course begins. Screenshots of this survey can be found in appendix A. Students will not be "recruited" to take the survey. It is fully optional. There is no additional consent form provided along with the survey. Consent for this survey is covered by the standard edX Terms of Service Agreement and Privacy Policy.

An additional survey question to be inserted will ask whether individuals taking the course will be willing to participate in follow up interviews. From this pool, users will be selected for the qualitative interviews.

All participants selected for interviews and additional surveys will first sign an additional research consent form. This additional consent form has been developed from HRP-502a – TEMPLATE CONSENT SOCIAL BEHAVIORAL template document. (See the attached form labelled: Meaney student_interview CONSENT DOCUMENT and Meaney producer_interview CONSENT DOCUMENT)

13 Training

Provide the date(s) the members of the research team have completed the CITI training for human participants. This training must be taken within the last 4 years. Additional information can be found at: Training.

Michael J. Meaney 9-14-2017

[redacted]

[redacted]

Fwd: STUDY00007005 has been approved

Michael J. Meaney <mjm234@cam.ac.uk>

[redacted]

To: Michael J. Meaney <mj.meaney@gmail.com>; M.J. Meaney <mjm234@hermes.cam.ac.uk>

[redacted]-- doing some work on my quals. I am likely going to have some of my

---------- Forwarded message ---------

[redacted]

Date: Mon, Dec 4, 2017 at 8:59 AM

Subject: Fwd: STUDY00007005 has been approved

To: [redacted], <mjm234@cam.ac.uk>

Pat

Begin forwarded message:

From: [redacted]

Date: December 4, 2017 at 6:37:06 AM MST

To: [redacted]

Subject: STUDY00007005 has been approved

Reply-To: [redacted]

Template:IRB_T_Post-Review_Approved

Notification of Approval

To:	[redacted]
Link:	STUDY00007005
P.I.:	[redacted]
Title:	MOOCs and Educational Equity
	This submission has been approved. You can access the correspondence letter using the following link:
Description:	Correspondence_for_STUDY00007005.pdf(0.01)
	To review additional details, click the link above to access the project workspace.

--

Michael J. Meaney

Appendix 3.3: Interviewee Consent Form

STUDY TITLE: MOOCs and Educational Equity

I am a Mike Meaney, a PhD student at the University of Cambridge and visiting research fellow in the [redacted]. I am conducting a research study to examine the implications of MOOCs for educational inequity; I am leveraging data from the [redacted] to do so.

I am inviting your participation, which will involve a semi-structured interview to aimed to help us discover how you are conceptualizing the notion of "educational equity" in the design and production of [redacted]. You have the right not to answer any question, and to stop participation at any time. This interview will take approximately one hour.
Users selected for interviews will be linked to their demographic, survey, and user activity. This information may be referenced during the interview. An anonymous data key will be used to link the survey information to the user activity information, likely [redacted]

Your participation in this study is voluntary. If you choose not to participate or to withdraw from the study at any time, there will be no penalty. You must be 18 or older to participate in the study.

Although there are no possible benefits of your participation are, there are no foreseeable risks or discomforts to your participation.

All of your responses and course work during this study will be kept confidential and organized by an anonymous subject number and NOT your name. In other words, your name will neither be recorded nor maintained with the data collected in this experiment. The results of this study may be used in chapters, reports, presentations, or publications, but your name will not be used.
I would like to audio record this interview. The interview will not be recorded without your permission. Please let me know if you do <u>not</u> want the interview to be recorded; you also can change your mind after the interview starts, just let me know.
If you have any questions concerning the research study, please contact the research team at: Mike Meaney, Visiting Research Fellow, [redacted] . If you have any questions about your rights as a subject/participant in this research, or if you feel you have been placed at risk, you can contact the [redacted], through the [redacted] Please let me know if you wish to be part of the study.

By signing below, you are agreeing to be part of the study.
Name:
Signature: Date:

Appendix 4.1: Classification of Research Areas in Distance Education (Zawacki-Richter, 2009)

Macro level: Distance education systems and theories.

1. Access, equity, and ethics: The democratisation of access to distance education afforded by new media and by finding ways to deliver high-quality education to those who have limited resources and poor infrastructure; issues that refer to the (sustainable) provision of distance education in developing areas. What is the impact of distance education (e.g., via mobile learning) on narrowing the digital divide and what is the role of ICT (information and communication technologies) and/or OER (open educational resources) in terms of access to education?
2. Globalisation of education and cross-cultural aspects: Aspects that refer to the global external environment and drivers, the development of the global distance education market, teaching and learning in mediated global environments, and the implications for professional development.
3. Distance teaching systems and institutions: Distance education delivery systems, the role of institutional partnerships in developing transnational programmes, and the impact of ICT on the convergence of conventional education and distance education institutions (hybrid or mixed mode).
4. Theories and models: Theoretical frameworks for and foundations of distance education, e.g., the theoretical basis of instructional models, knowledge construction, interaction between learners, or the impact of social constructivism learning theories on distance education practice.
5. Research methods in distance education and knowledge transfer: Methodological considerations, the impact of distance education research and writing on practice, and the role of professional associations in improving practice. Literature reviews and works on the history of distance education are also subsumed within this area.

Meso level: Management, organization, and technology.

6. Management and organization: Strategies, administration, and organizational infrastructures and frameworks for the development, implementation, and sustainable delivery of distance education programmes. What is required for successful leadership in distance education? Distance education and policies relating to continuing education, lifelong learning, and the impact of online learning on institutional policies, as well as legal issues (copyright and intellectual property).
7. Costs and benefits: Aspects that refer to financial management, costing, pricing, and business models in distance education. Efficiency: What is the return on investment or impact of distance education programmes? What is the impact of ICT on the costing models and the scalability of distance education delivery? How can cost effective but meaningful learner support be provided?
8. Educational technology: New trends in educational technology for distance education (e.g., Web 2.0 applications or mobile learning) and the benefits and challenges of using OERs, media selection (e.g., synchronous vs. asynchronous media), technical infrastructure and equipment for online learning environments, and their opportunities for teaching and learning.
9. Innovation and change: Issues that refer to educational innovation with new media and measures to support and facilitate change in institutions (e.g., incentive systems for faculty, aspects referring to staff workloads, promotion, and tenure).
10. Professional development and faculty support: Professional development and faculty support services as a prerequisite for innovation and change. What are the competencies of online teachers and how can they be developed?
11. Learner support services: The infrastructure for and organization of learner support systems (from information and counselling for prospective students about library services and technical support to career services and alumni networks).
12. Quality assurance: Issues that refer to accreditation and quality standards in distance education. The impact of quality assurance and high-quality learner support on enrolments and dropout/ retention, as well as reputation and acceptance of distance education as a valid form of educational provision.

Micro level: Teaching and learning in distance education.

13. Instructional design: Issues that refer to the stages of the instructional design process for curriculum and course development. Special emphasis is placed on pedagogical approaches for tutoring online (scaffolding), the design of (culturally appropriate) study material, opportunities provided by new developments in educational technology for teaching and learning (e.g. Web 2.0 applications and mobile devices), as well as assessment practices in distance education.
14. Interaction and communication in learning communities: Closely related to instructional design considerations is course design that fosters (online) articulation, interaction, reflection, and collaboration throughout the learning and teaching process. Special areas include the development of online communities, gender differences, and cross-cultural aspects in online communication.
15. Learner characteristics: The aims and goals of adult learners, the socioeconomic Background of distance education students, their different learning styles, critical thinking dispositions, and special needs. How do students learn online (learner behaviour patterns, learning styles) and what competencies are needed for distance learning (e.g. digital literacy")?

Appendix 5.1: Supplementary Analysis for Chapter 5

Of the 29,083 learners included in the cluster analyses presented in **Chapter 5**, some 21 percent did not provide educational background data. The Gower Distance-based cluster analyses utilise education background as a key variable in computing the distance between clusters. Initially, I did not consider imputing the data because I did not think leaving the data as unknown detracted from the analysis, as it is clear that educational background levels did indeed impact the clustering, represented by the other clusters. Determining whether this was the case was the primary objective of the analysis.

The analysis most at risk of including the Unknown variable level, the Gower-distance based clustering, is impacted in a predictable way. Namely, the Dice Coefficient component of Gower distance will separate clusters along binary dimensions of categorical variables. This is indicated when deriving the number of ideal clusters to utilise in the analysis via evaluating the Silhouette widths. When Unknown is excluded from the analysis, four clusters are derived, two for each education background level, College Plus and No College. This is represented in **Figure A5.1** and **Table A5.1**, which confirm that the four clusters contain groups of higher achieving and lower achieving College Plus learners, and groups of higher achieving and lower achieving No College learners.

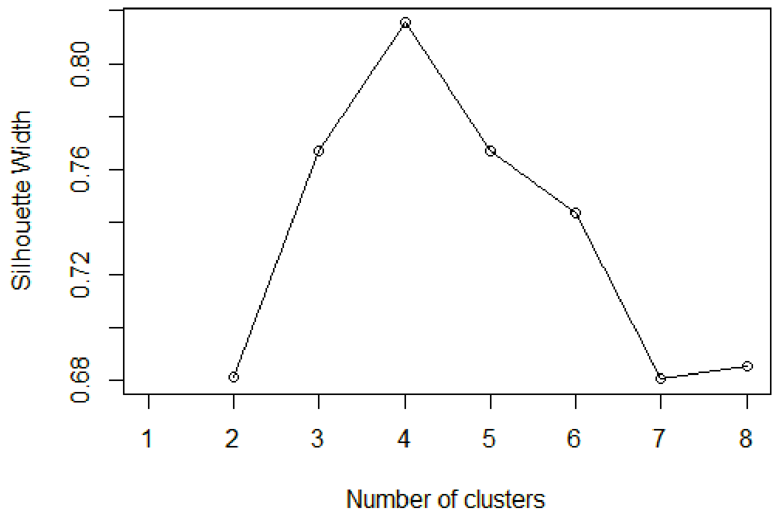


Figure A5.1: Silhouette plot of the PAM clustering algorithm for k=2:8, excluding Unknown education level data. At four clusters, the average silhouette width for the data objects is above .8, indicating sound clusters. Total N = 23,305, excluding all Unknown education level data.

Table A5.1: Descriptive statistics of the four clusters determined by the PAM algorithm, excluding Unknown education level data: College Plus All-rounders (10.4 percent), College Plus Disengagers (55 percent), No College All-rounders (7.4 percent), No College Disengagers (27.1 percent. Total N = 23,305, excluding all Unknown education level data.

Characteristic	**Overall**, N = 23035	**College Plus, All-rounders**, N = 2411[1]	**College Plus, Disengagers**, N = 12673[1]	**No College, All-rounders**, N = 1710[1]	**No College, Disengagers**, N = 6241[1]
Education_Level					
College Plus	15084 (65%)	2411 (100%)	12673 (100%)	0 (0%)	0 (0%)
No College	7951 (35%)	0 (0%)	0 (0%)	1710 (100%)	6241 (100%)
Part_and_Perf	0.05 (0.02, 0.24)	0.87 (0.60, 0.95)	0.04 (0.02, 0.09)	0.71 (0.52, 0.94)	0.04 (0.02, 0.11)
Percent_Grade	0.01 (0.00, 0.13)	0.87 (0.74, 0.93)	0.00 (0.00, 0.03)	0.84 (0.64, 0.92)	0.00 (0.00, 0.04)
event_count.x_logged	6.34 (5.34, 7.56)	8.32 (7.96, 8.71)	5.94 (5.14, 6.78)	8.39 (8.05, 8.73)	6.12 (5.19, 6.99)
Event_Count_total	564 (209, 1910)	4122 (2864, 6084)	381 (171, 881)	4384 (3133, 6191)	455 (179, 1084)
Relative_Grade_to_Engagement_Ratio	0.17 (0.00, 0.65)	0.98 (0.89, 1.13)	0.00 (0.00, 0.35)	0.99 (0.86, 1.61)	0.00 (0.00, 0.38)

[1] Statistics presented: n (%); median (IQR)

When Unknown is included, six clusters are derived, two for each education background level, College Plus, No College, and Unknown. These conclusions are represented in **Figure 5.10 and Table 5.6** from the original analysis**.**

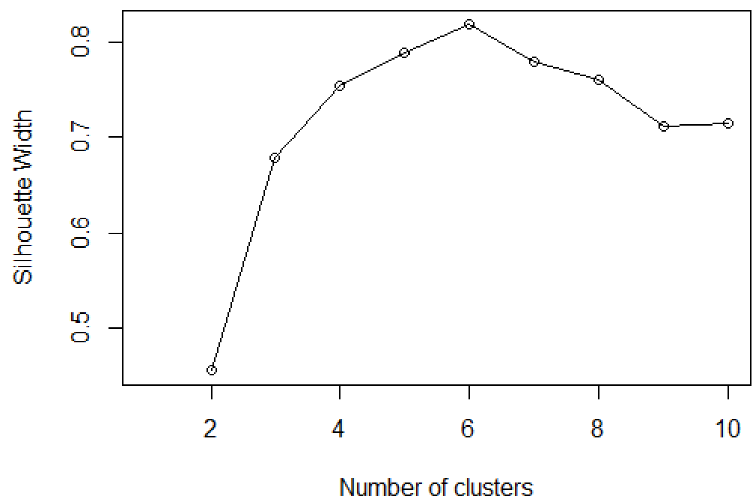


Figure 5.10: Silhouette plot of the PAM clustering algorithm for k=2:10. At six clusters, the average silhouette width for the data objects is above .8, indicating sound clusters. N = 29,083, including all Unknown education level data.

Table 5.6: Descriptive statistics of the six clusters determined by the PAM algorithm: College Plus All-rounders (8.3 percent), College Plus Disengagers (44 percent), No College All-rounders (5.9 percent), No College Disengagers (21 percent), Unknown All-rounders (3.2 percent), and Unknown Disengagers (18 percent). Total N = 29,083, including all Unknown education level data.

Characteristic	**Overall**, N = 29083	**College Plus, All-rounders**, N = 2411[1]	**College Plus, Disengagers**, N = 12673[1]	**No College, All-rounders**, N = 1710[1]	**No College, Disengagers**, N = 6241[1]	**Unknown, All-rounders**, N = 942[1]	**Unknown, Disengagers**, N = 5106[1]
Education_Level							
College Plus	15084 (52%)	2411 (100%)	12673 (100%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)
No College	7951 (27%)	0 (0%)	0 (0%)	1710 (100%)	6241 (100%)	0 (0%)	0 (0%)
Unknown	6048 (21%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)	942 (100%)	5106 (100%)
Part_and_Perf	0.05 (0.02, 0.23)	0.87 (0.60, 0.95)	0.04 (0.02, 0.09)	0.71 (0.52, 0.94)	0.04 (0.02, 0.11)	0.78 (0.54, 0.92)	0.03 (0.02, 0.08)
Percent_Grade	0.01 (0.00, 0.11)	0.87 (0.74, 0.93)	0.00 (0.00, 0.03)	0.84 (0.64, 0.92)	0.00 (0.00, 0.04)	0.85 (0.66, 0.92)	0.00 (0.00, 0.01)
Event_Count_total	547 (202, 1850)	4122 (2864, 6084)	381 (171, 881)	4384 (3133, 6191)	455 (179, 1084)	4444 (3162, 6224)	366 (141, 849)
Relative_Grade_to_Engagement_Ratio	0.12 (0.00, 0.61)	0.98 (0.89, 1.13)	0.00 (0.00, 0.35)	0.99 (0.86, 1.61)	0.00 (0.00, 0.38)	0.99 (0.86, 1.48)	0.00 (0.00, 0.23)

[1] Statistics presented: n (%); median (IQR)

The second important consideration stems from the inclusion of SES data. Specifically, only a small sample of SES data from the USA is available for analysis. This data is represented alongside the entire ‘committed learner’ data set, including data from outside the USA. It could be potentially problematic to cluster on entire world data and then represent SES data from only the USA, especially if the clustering results would be different between entire world data and USA-only data. When limiting the Gower Distance-based cluster analysis to USA data only, six clusters are found, extremely similar to the six clusters found across the full sample of ‘committed learners;’ thus there was no need to differentiate the clustering results further.

Limiting the Gower Distance based cluster analysis data to USA data only, six clusters are found to be appropriate according to Silhouette width analysis, represented in **Figure A5.2**, yielding extremely similar clusters, represented in **Table A5.2**.

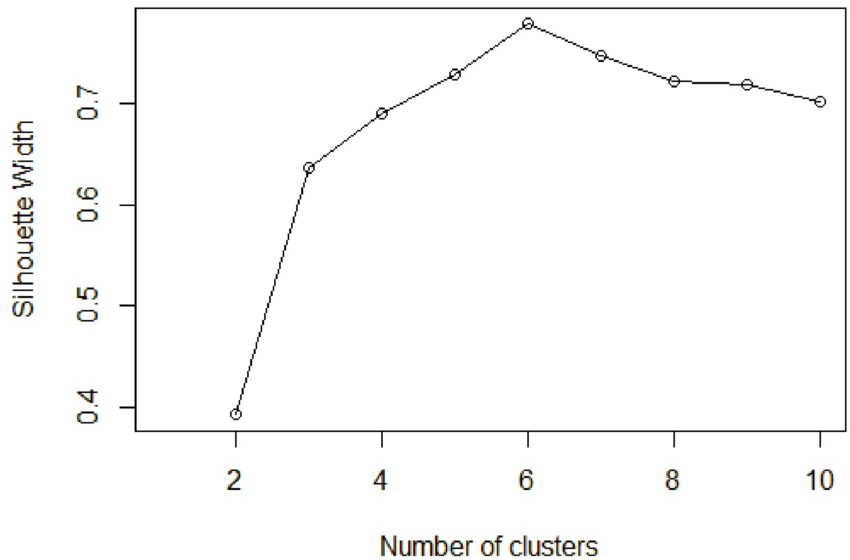


Figure A5.2: Silhouette plot of the PAM clustering algorithm for k=2:10, USA-only data. At six clusters, the average silhouette width for the data objects is well above .7 indicating sound clusters. Total N = 9,708, including only USA data.

Table A5.2: Descriptive statistics of the six clusters determined by the PAM algorithm, USA-only data: College Plus All-rounders (6.7 percent), College Plus Disengagers (28.4 percent), No College All-rounders (11.3 percent), No College Disengagers (28 percent), Unknown All-rounders (5.5 percent), and Unknown Disengagers (20.3 percent). Total N = 9,708, including only USA data.

Characteristic	**Overall**, N = 9708	**College Plus, All-rounders**, N = 654[1]	**College Plus, Disengagers**, N = 2761[1]	**No College, All-rounders**, N = 1097[1]	**No College, Disengagers**, N = 2681[1]	**Unknown, All-rounders**, N = 541[1]	**Unknown, Disengagers**, N = 1974[1]
Education_Level							
College Plus	3415 (35%)	654 (100%)	2761 (100%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)
No College	3778 (39%)	0 (0%)	0 (0%)	1097 (100%)	2681 (100%)	0 (0%)	0 (0%)
Unknown	2515 (26%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)	541 (100%)	1974 (100%)
Part_and_Perf	0.08 (0.02, 0.37)	0.83 (0.56, 0.95)	0.04 (0.02, 0.11)	0.59 (0.48, 0.90)	0.05 (0.02, 0.14)	0.76 (0.54, 0.92)	0.03 (0.02, 0.11)
Percent_Grade	0.02 (0.00, 0.30)	0.87 (0.72, 0.94)	0.00 (0.00, 0.04)	0.83 (0.63, 0.91)	0.01 (0.00, 0.05)	0.85 (0.69, 0.91)	0.00 (0.00, 0.03)
event_count.x_logged	6.66 (5.54, 7.90)	8.36 (7.97, 8.77)	6.03 (5.19, 6.94)	8.38 (8.04, 8.73)	6.34 (5.38, 7.17)	8.43 (8.11, 8.76)	6.07 (5.14, 6.91)
Event_Count_total	784 (254, 2704)	4264 (2890, 6468)	417 (179, 1033)	4350 (3115, 6202)	564 (216, 1300)	4561 (3328, 6371)	433 (170, 1001)
Relative_Grade_to_Engagement_Ratio	0.25 (0.00, 0.82)	0.99 (0.89, 1.31)	0.00 (0.00, 0.41)	1.03 (0.87, 1.69)	0.14 (0.00, 0.42)	1.00 (0.86, 1.58)	0.00 (0.00, 0.25)

[1] Statistics presented: n (%); median (IQR)

When the entire data set is analysed, six extremely similar clusters are derived, two for each education background level, College Plus, No College, and Unknown. These conclusions are represented in **Figure 5.10 and Table 5.6** from the original analysis**.**

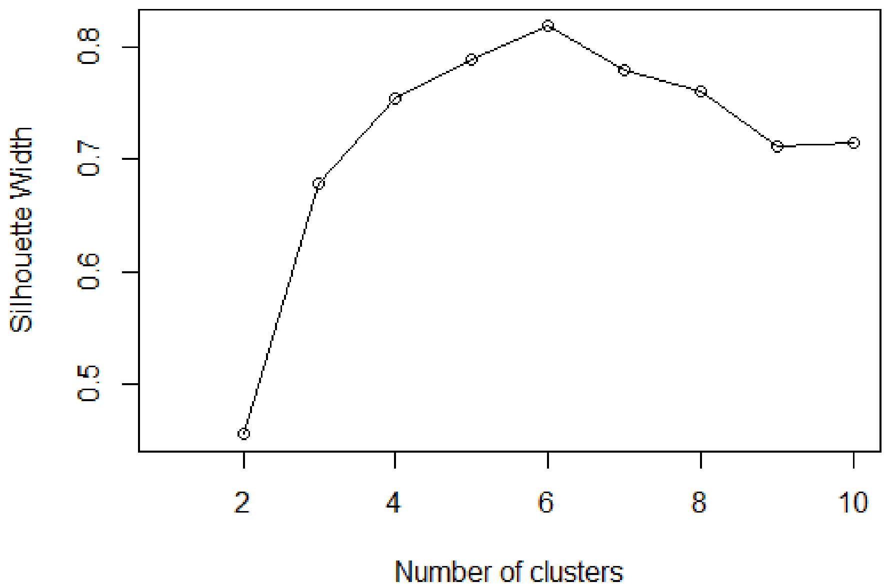


Figure 5.10: Silhouette plot of the PAM clustering algorithm for k=2:10. At six clusters, the average silhouette width for the data objects is above .8, indicating sound clusters. N = 29,083, including all Unknown education level data.

Table 5.6: Descriptive statistics of the six clusters determined by the PAM algorithm: College Plus All-rounders (8.3 percent), College Plus Disengagers (44 percent), No College All-rounders (5.9 percent), No College Disengagers (21 percent), Unknown All-rounders (3.2 percent), and Unknown Disengagers (18 percent). Total N = 29,083, including all Unknown education level data.

Characteristic	**Overall**, N = 29083	**College Plus, All-rounders**, N = 2411[1]	**College Plus, Disengagers**, N = 12673[1]	**No College, All-rounders**, N = 1710[1]	**No College, Disengagers**, N = 6241[1]	**Unknown, All-rounders**, N = 942[1]	**Unknown, Disengagers**, N = 5106[1]
Education_Level							
College Plus	15084 (52%)	2411 (100%)	12673 (100%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)
No College	7951 (27%)	0 (0%)	0 (0%)	1710 (100%)	6241 (100%)	0 (0%)	0 (0%)
Unknown	6048 (21%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)	942 (100%)	5106 (100%)
Part_and_Perf	0.05 (0.02, 0.23)	0.87 (0.60, 0.95)	0.04 (0.02, 0.09)	0.71 (0.52, 0.94)	0.04 (0.02, 0.11)	0.78 (0.54, 0.92)	0.03 (0.02, 0.08)
Percent_Grade	0.01 (0.00, 0.11)	0.87 (0.74, 0.93)	0.00 (0.00, 0.03)	0.84 (0.64, 0.92)	0.00 (0.00, 0.04)	0.85 (0.66, 0.92)	0.00 (0.00, 0.01)
Event_Count_total	547 (202, 1850)	4122 (2864, 6084)	381 (171, 881)	4384 (3133, 6191)	455 (179, 1084)	4444 (3162, 6224)	366 (141, 849)
Relative_Grade_to_Engagement_Ratio	0.12 (0.00, 0.61)	0.98 (0.89, 1.13)	0.00 (0.00, 0.35)	0.99 (0.86, 1.61)	0.00 (0.00, 0.38)	0.99 (0.86, 1.48)	0.00 (0.00, 0.23)

[1] Statistics presented: n (%); median (IQR)

Finally, the distribution of learners with available SES background is similar across the USA-only clusters and the entire world clusters. **Table A5.3** represents the multinomial logistic regression output of USA-only data where SES is the explanatory variable, and cluster is the outcome variable. **Table 5.8** is from the original analysis, indicating similar results; notably, that users from lower SES backgrounds are no less likely to be in any of the clusters compared to their higher SES peers.

Table A5.3: Relative Risk Ratios: Socioeconomic Status (SES) and Cluster, USA-only data. The relative risk ratios, shown as the exponentiated value of the logit coefficients from the multinomial logistic regression, where SES is the explanatory variable, and cluster is the outcome variable. College Plus, All-rounders from Mid-High SES backgrounds are the reference group. Total N = 9,708, including only USA data.

	Dependent variable:				
	College Plus, Disengagers	No College, All-rounders	No College, Disengagers	Unknown, All-rounders	Unknown, Disengagers
	(1)	(2)	(3)	(4)	(5)
bi_SES_status_finalUnknown SES	1.167	0.490^{***}	0.818	0.262^{***}	0.654^{***}
	(0.124)	(0.131)	(0.122)	(0.144)	(0.124)
bi_SES_status_finalLow SES	0.934	1.213	1.255	1.470	1.447
	(0.285)	(0.286)	(0.272)	(0.293)	(0.273)
Constant	3.718^{***}	2.864^{***}	4.781^{***}	2.041^{***}	4.145^{***}
	(0.115)	(0.119)	(0.112)	(0.125)	(0.114)
Akaike Inf. Crit.	31,279.030	31,279.030	31,279.030	31,279.030	31,279.030
Note:					*p<0.1; **p<0.05; ***p<0.01

Table 5.8: Relative Risk Ratios: Socioeconomic Status (SES) and Cluster. The relative risk ratios, shown as the exponentiated value of the logit coefficients from the multinomial logistic regression, where SES is the explanatory variable, and cluster is the outcome variable. College Plus, All-rounders from Mid-High SES backgrounds are the reference group. Total N = 29,083.

	Dependent variable:				
	College Plus, Disengagers	No College, All-rounders	No College, Disengagers	Unknown, All-rounders	Unknown, Disengagers
	(1)	(2)	(3)	(4)	(5)
bi_SES_status_finalUnknown SES	1.376^{***}	0.229^{***}	0.544^{***}	0.160^{***}	0.518^{***}
	(0.111)	(0.119)	(0.110)	(0.128)	(0.112)
bi_SES_status_finalLow SES	0.909	1.257	1.259	1.471	1.428
	(0.270)	(0.274)	(0.260)	(0.282)	(0.261)
Constant	3.878^{***}	2.613^{***}	4.538^{***}	1.877^{***}	3.868^{***}
	(0.109)	(0.114)	(0.107)	(0.120)	(0.109)
Akaike Inf. Crit.	85,200.670	85,200.670	85,200.670	85,200.670	85,200.670
Note:					*p<0.1; **p<0.05; ***p<0.01

Appendix 6.1: Codebook for Thematic Analysis of Interviews; Global to Basic Themes

Research Question	Global Themes	Organizing Themes	Themes	Description of Theme	Illustrative Example from Interview Transcripts
R1: How do producers conceptualize inclusion?	Global Theme 1: Diverse Conceptualizations of Concern for Inclusion	Explicit Articulation of Concern for Inclusion	Diverse End User Concepts	Producers articulated broad and diverse descriptions of who they consider to be their end-using student, with some discrepancies among themselves.	"I think of everybody… I know We have had students who went through our earned admissions track because they didn't have the qualifications to get into [host university] online. So, they use [mooc program] as a pathway to get into [host university]. Women who have children or families. All that. So, I just kind of think of – I encompass everybody. I don't want to discriminate between – people with ages between 18 and 27 – I just think of everybody."
			Mission of University	Producers described the institutional commitment of the university to providing high quality educational experiences to as an inclusive definitions of learners as possible to be inspiring and motivating.	"Yeah it's like it's part it's our part of the mission statement right — it's not about who we exclude it's about who we include — and that's one of the most heartening things about working for [host university] is that is — especially in [mooc program] — that is like core to how this thing works and it's super exciting."
			Realities of Student Life (non-financial)	Stories of real students, and the various challenges and barriers they face and overcome, were a source of inspiration and design-orientation for the producers.	"There are certainly students that have personal backstories. There are some students — we had a person go in our earned admission program, it was a lady that had started college and in her first term her father died. He was the breadwinner for that household, and she had to; she couldn't withdraw she got like a 1.0 or something. She was no longer — she had to take like a couple years off and work. After that she tried to get back into college and they're like you have a 1.0, no. So very intelligent young lady once she was able to take these classes she got like straight A's. And she's now getting straight A's at [host university]."
			Cost Barriers to Higher Education	The high cost barrier to higher education and the risk this imposes on students was cited a design constraint for they built their programs.	"Give them that kind of early perspective at a low cost and see if it's that like interesting to them, low risk, low cost. And they could take it for free and audit it and see if that's what they want to do."
		Personal and Professional Background Play a Significant Role	Personal Experiences and Values	Personal experiences drawing them to a career in education, as well as other personal values, were described as reasons for committing to inclusion.	"I am inspired by Gandhi - yeah Gandhi was all about supporting the masses right like don't leave the masses behind. And we — it's so easy to try to just look for the upper echelon of our culture but we need to really take a step back and say we all win if we support all of humanity. And so, with that in mind we have to look at education as how can we do this for everyone. And it's only being exasperated as we move forward into a digital age that requires this knowledge."
			Education background	Producers cited extensive academic backgrounds in education or subject matter expertise as informative to their pedagogy.	"So, I looked into working as an ID and went back to [host university] for a degree in ed Tech. And at that time, they had two tracks. One ed tech for classroom teachers and ed tech for instructional designers. So, I took the ID route."
			Work experience, including private sector experiences	A broad array of work experiences, including considerably time in the private sector and at for-profit colleges, provided ample lessons and cautions that informed their practice.	"We do have a lot of staff that have come from University of Phoenix and with I mean you mentioned the market perception and the backlash and the negative connotations associated what the University of Phoenix. One thing that they don't get enough credit for are the internal processes, the technology, the systems, the people."
R2: What processes and practices do they engage in to make design inclusive?	Global Theme 2: Innovative Pedagogy and Program Design	Teaching and Learning Methods	Explicit Learning Philosophies and Design Principles	Producers explicitly detailed their teaching and learning philosophies as guiding how they built their courses, often mentioning explicitly frameworks and strategies to account for the different needs and abilities of various learners.	"You only get to do something when you do the project and that's not really our philosophy of how you learn. You only learn by doing. So, we wanted to make the class very much focused on — you watch something you read something you do something. And you do that over and over and over — a hundred times before you get to the project and then you do something again."
			Engaging Teaching Methods	Producers sought to embed numerous examples of engaging content into their courses, including: real-world relevant course content, interactive pedagogy, peer-to-peer learning opportunities, personalized and adaptive instruction.	"It was it was in the midst of it. one of the things that we put in our original design was industry moments. The idea was to tie whatever it is that they're learning right now to what is useful and what is used in industry and to put rea face on it. And that's kind of like the treat at the end of every major section. We did a bunch of visits to some Computer History Museum's to show some cool stuff about how we got here and then it's like we did some career stuff at the same time and so they're usually - one or two little videos at the end that are that are like that kind of like Discovery Channel / / you know inspirational personal inspirational stories type of things. And that was the very first row in the classroom to make sure that was built into it."
		Program Design	Provide Pathway to University for all students	The MOOC program provided an opportunity to earn formal entry to the university if certain criteria were met; this is provided as an alternative pathway to admission, even for students initially denied.	"So, what this is is students that would otherwise be denied admission to [host university], we say you take these four classes or eight classes depending on your age and we will guarantee you can get into [host university]. So, we're no longer going to deny any students to [host university]."
			Curated and Creative Student Support Mechanisms	Various student support mechanisms enhanced the user experience, from adaptive emailing techniques and pleasing user interface design, to a formal student support coaching infrastructure (in early development at the time).	"They do, we have a whole library of email templates that are sent out at certain points in time, we are being proactive and telling them what to expect and giving them this as clear and as much information as possible but it goes back to people don't read emails anymore, they don't prefer this so we have to be able to supplement that with chat and with phone."
	Global Theme 3: Operational Practices and Processes, Influenced by Third Space Actors	Opportunities and Constrains	Corporate Partners	Extensive corporate partnerships, from platform and curriculum providers, to employee benefit partners, were an integral feature of MOOC and program construction, presenting both opportunities and challenges.	"And then, that's but because there's not a lot of funds to promote [mooc program], there's a lot of digital acquisition to do, so the more analytics and there's a big problem that [mooc program], Global Freshman Academy courses initially just sat on edX org, which is a platform that we don't own."
			Collaborative, Diffuse Processes	Producing the MOOCs required substantial collaboration within the university and externally.	"I have no idea." (Professor responding to the question about recruiting students)
			Financial Sustainability of Program	Simply put, the MOOCs and program needed to be financially sustainable over the long run.	"I've also helped on finding the value proposition so that we could make this a financially feasible endeavor that [host university] could have work long-term."
		Iterative Processes	Evidence based practices, including student feedback	Extensive use of data analytics, student feedback, and intentional reflection on what was successful is incorporated.	"So, we know for example if the student is going to leave the university, it's usually going to be within the first four classes and to look at it as a line graphic, it usually happens in the first or the second class. If it doesn't happen in the first or the second class then it's the third or the fourth. If we keep them beyond the four session it goes drastically down."
			Future Aspirations	A general commitment to learning from past lessons as well as ambitious visions for future product and program iterations were common.	"So, there's there are all these ideas that are sort of floating around right now people are trying all these radically different things and we've just like scratched the surface with our pretty pictures and interactive things, which is still a big step forward for computer science. So, there's a lot of stuff that we want to try to do."

Appendix 6.1: Codebook for Thematic Analysis of Interviews; Codes to Initial Themes

Codes	Description of Code	Illustrative Example from Interview Transcripts	Initial themes
End User Concepts	Description of the end user they think of	"You know, I'm interested in looking at factors like single mother, if they are working adult, if they are older than 26 sort of types of learners that need more flexible designs to support their learning and that don't sort of make up the mean learner that people think about."	End User Concepts
Desire to Upskill	Mention of learners looking to upskill or change careers	"So, what this will teach them is real skills as far as how to use Excel, how to build charts, and do things like do some data analysis. These are things that they could work — they use at a current job today. And skills that could help them get a raise, and promote them, as something that they're going to college, and they they can advance and get benefit from it in seven weeks. So, we are looking at that."	
Student Sub Groups	Description of student sub group	"Yeah so that was actually my next goal. We know our course structure is supporting a variety of learners because we know that the people that take the class are going to be like the people that we talked about right? The people that are looking for a career change, they're already successful they already know how to college so to speak yeah and and have already developed those study skills. But we also know that there's people that are going to be in the class that have none of those skills. They're like the first time sort of people. And then there are the people that are even sort of less. So, I think we categorized them by goals — explorers, personal developers, and academic."	
Traits of successful students	Characteristics and behaviors of students who succeed in MOOC	"So, what we found is we needed to have students that were truly motivated, that would allow them to get through these classes."	
Mission of [host university]	Referencing the charter of the university or president	"We really think that [host university]'s mission isn't just to give these classes but to actually get students to complete these classes and to convert to actual [host university] credit."	Mission of [host university]
Proud of	What makes them proud of their MOOC work	"I'm super proud of the investment in the hard stuff that we've made."	
Empathy	Descriptions of placing themselves into the lives of the learners	"So, you can put a name to a face where it's not just a profile page on a website, it's an actual video with them talking so that they can humanize them a little bit."	
Trust	Practices that seek to establish trust with students	"I mean you want to stay realistic and positive but it's also being realistic where something is going to happen throughout your degree program. When it does are you going to be prepared to you know to deal with that and do you know who I am and what I do and what I can help you with."	
Honesty	Practicing transparency with students	"So I think for [host university], they don't dangle the carrot of financial and you can go to school for free. So they're more upfront and they're honest."	
Promoting the [host university] Model	Descriptions of times when they could promote the model of their university	"That was a highlight for sure I was able to go to New York City and Washington DC to listen to Howard Schultz speak, and to announce it to Starbucks and to the public. So those are certainly some highlights that stand out."	
Cost barriers for students	High costs of education, school debt discussed	"Giving everyone that wants an opportunity to get a degree, that opportunity at a reasonable price that's not going to put them in debt until they're forty-five or fifty."	Cost Barriers for Students
Meet people where they are	Seeking to meet students where they are, lower barriers to entry	"Students can connect with other students; students can connect with staff and we're starting to send you know text messages to students. Text, chat, phone, email, so to keep, you have to meet people where they are at."	
Editorial comment on cost	High costs of education, school debt discussed	"As a person, an individual, I think the amount of debt people take out for school is gross and they don't look at as in terms of investment for future, maybe not completely."	
Value prop for students	Students can connect with the value prop of education	"Yeah, I think that something that higher ed in general needs to provide is how is this going to actually impact my monetary life after this?"	
Student Realities	Descriptions of the lives of real or hypothetical students to frame access and inclusion issues	"And we know that that's important for students to be able to keep their eye on the price to get to the finish line."	Student Realities of Life
Anecdotes of Students	Descriptions of the lives of real or hypothetical students to frame access and inclusion issues	"And she was excited to hear about the prospect because she didn't graduate from high school. So by default, she can't get into university."	
Initial Approach to MOOC Design	Considerations made at the beginning of the design process	"We were looking at this as a way to open education to the masses, to many more people."	Initial Approach to MOOC Design
Professional Work Experience	How experiences from their previous jobs informed their approach	"Before I came to [host university], I was at an agency here doing digital strategy, advertising, and marketing campaigns."	Influence of Professional Background
For profit university background – some good lessons	Interesting and valuable lessons learned from time working at for profits	"We do have a lot of staff that have come from University of Phoenix and with I mean you mentioned the market perception and the backlash and the negative connotations associated what the University of Phoenix. One thing that they don't get enough credit for are the internal processes, the technology, the systems, the people."	
Concern about for profit exploitive capacities	Descriptions of negative things about for profit practices	"So that's why that was one of my big pushes to get out of for profit because that's how they sell, the education is here's this grandiose dream, you can do it, anybody can achieve it, and then we're going to help you get there but then if you fail at your classes because life gets on the way, you're in huge debt, and I just couldn't, couldn't, yeah."	
Design experience	Experiences with designing curriculum or interfaces for educational technologies	"So I got to work with the couple of the deans to think of more user-friendly approach to the LMS and link the basic thing of linking."	
Student support services background	Descriptions of previous work experiences supporting students	"I've graduated from NAU with my undergrad in business with the certificate in marketing communication and promotion and so started as an advisor, working my way up to director."	
Personal Life Experience	Personal anecdotes that informed their inspiration or motivation	"Both my parents were first time like the first in their families to get a college education. Both my mother and father. So, I was raised with a strong, you know, focus on education being important."	Influence of Personal Background
Education Background Experience	Studying education of a subject matter informed how they approached teaching and learning		Influence of Educational Background
Educational Background helps inform MOOC design	Studying education of a subject matter informed how they approached building MOOCs	"My experience was — I was looking at this and my ideal was — I took a class on a particular set of artificial intelligence algorithms from Udacity. There's one of the early classes that they offered."	
How they got involved	The circumstances under which they became involved making MOOCs	"So, I looked into working as an ID and went back to [host university] for a degree in ed Tech. And at that time, they had two tracks. One ed tech for classroom teachers and ed tech for instructional designers."	
Initial MOOC concerns	Initial concerns producers had with the MOOCs experiment	"It's really hard, especially with moocs. If they're going to drop out, they do it within the first two weeks."	How they became involved
Excited at prospect of MOOCs	Excitement that producers had about the prospects of MOOCs	"And then so this class comes along and it's fully online it's you know [MOOC program] — we're excited about access."	
General comment on online learning	General comments and thoughts about the opportunities and challenges of online learning.	"It's not [just] about access it's about elevating computer science."	
Editorial comment	Expressed opinion or belief as a person	"We would love to see from [inaudible] and let people know there's other way to enter college because I personally, me as an individual, think that like four-hour test in the SAT or ACT exams are not indicative in anyway about your academic performance, nor as an individual, so why we put so much weight in those two horrible things."	
Learning Philosophy in Action	Expression of a coherent learning philosophy, and examples of implementation of that	" I... when I was looking at where I align myself, I definitely was more in the constructivist kind of realm because I wanted to start with that foundation and you build that foundation and, you know, you then create the next, the next, then you scaffold off of each other that again, it's a big buzzword right now but that community of learning, learning from each other and select from the instructor like I would try as much as I could to get the students to learn from themselves."	Learning Philosophy in Action
Interactive Pedagogy	Examples of integrating interactive components into course design	"The instructor decided he wanted to create and build in Python code, an interactive textbook."	
Real Life Application	Examples of using real world applications to make content more engaging	"It's working out problems and I actually was just trying to get the faculty to get a better understanding of why you would want this real world to applications."	
Personalized	Examples of ways to personalize course content	"Personalizes it so once that occurs we know students are more successful if they take orientation they're more likely to succeed. So that's one thing that they look for as soon as they register."	
Learning from Peers	Examples of ways that peer to peer learning were discussed	"I mean just imagine what you can learn from your peers when they're experiencing something completely different in another country; or they have a completely different world view or life experiences than you."	
Adaptive	Examples that of adaptive learning techniques incorporated into the courses	"So but it will be the same thing it's adaptive and it will have the same look and feel as 270 but yeah."	
Engagement Strategy	Examples of particularly engagement strategies used to improve the course	"We now have a CRM and use multiple instances of Salesforce to help us track and engage our students."	
Minimize Learning Curve of Tools	Comment about the selection of tools incorporated into courses	"Not really and that's I think why we pick the ones that we do." [Regarding learning curve of tools).	
Learning and Design Philosophy	Expression of a coherent learning philosophy and/or design principles that support this	"You only learn by doing. So, we wanted to make the class very much focused on — you watch something you read something you do something. And you do that over and over and over — a hundred times before you get to the project and then you do something again."	Learning and Design Philosophy
Desire to Support Students	Expresses a belief or describes a practice or mindset focused on supporting students	"You know every interaction with the student either your creating a barrier, or your removing one is really the way to look at. So, every interaction with the student is an opportunity to remove a barrier and using the coaching model as a framework not necessarily a template or a script."	Desire to Support Students
Motivation of Students	Discussion of student motivation and how that relates to success, how that can be stimulated	"But if they get a zero on it, a lot of them will shut down. But if we can kind of give them like carrot of where they're going, that goal in the end and why they should try and stick it out in this seven-and-a-half-week course?"	
Student Support Mechanisms	Description of specific student support mechanisms	"They do, we have a whole library of email templates that are sent out at certain points in time, we are being proactive and telling them what to expect and giving them this as clear and as much information as possible but it goes back to people don't read emails anymore, they don't prefer this so we have to be able to supplement that with chat and with phone."	
Inspiration and Motivation for students	Ways to increase motivation for students incorporated into the course	"So, it's like, "here is of some fun facts about you know how this came about and why this is," and all those kinds of weird stuff."	

Design Principles	Explicit mention or description of design principles guiding the course building process	"You want to be clean and consistent and simple and it connects with as many people as possible."	Design Principles
Opportunity to Innovate	Producers expressed a desire to innovate and saw the courses as a opportunity to be innovative	"And are given that opportunity to be innovative and to be creative and to work, keep throwing all these buzzwords and work collaboratively with the team instead of just one on one, you and a faculty and just try and get it."	
Academic Literature	Explicit reference of a concept from the academic literature	"When... it's a great question because we would look at that when I was working before in the master's program like what... where do you want to and in training, it's definitely just repeat over and over and over again so it's very behaviorist."	
User Experience Concerns	Expressed concerns about the user experience	" It's going to be an experience that is hopefully enjoyable, where it's meeting or exceeding their expectations."	
Pragmatic Approach	Expression of taking a practical approach to building courses and programs	"We do have some of that perspective and experience from the staff that we have in place as we think about what works and what does not work when it comes to engaging with students."	
Description of Program	Literal descriptions of how the program works	" So even students that are not admissible to [host university] have the opportunity to take classes through the Global Freshman Academy if they are under the age of 22 they have to take eight classes and obtain a 2.75 GPA or higher."	Description of program
Description of Course Content	Literal description of how the courses work, what they are composed of	"We have instructors who work with other third-party vendors, discovery lab in astronomy, what do they call it, Vocarian."	
Description of Staff Role	Literal description of the tasks of the producers I met with.	"So those are mine and then today, right before I met with you, I am working on... we just launched CIS 105 so that's my nine class. Yeah. So yeah, nice catalog."	
Constraints	Descriptions of challenges that had to be navigated during the building process	"They do, they have to meet you know they have to have TOEFL, if they're international they have to a high school diploma GED equivalent."	
User Acquisition	Descriptions of how students were acquired, of how this was thought about and conceptualized	" So it is key for lead gen in [host university], is we tag our website with pixels from [corporate partner], [corporate partner], LinkedIn, from our vendors. And then, fire them at appropriate stages in the funnel."	User Acquisition Processes and Insights
Description of Participation Funnel	Descriptions of the common drop out points along the way to successful completion	"So, we know for example if the student is going to leave the university, it's usually going to be within the first four classes and to look at it as a line graphic, it usually happens in the first or the second class."	
Look-a-like Marketing Strategy	User acquisition strategy	"And then you go to the other side of people who submit an RFI, people who then now start an application, and submit an application, who got accepted, who enrolled in their initial course. For them, the funnel the people are more valuable to us and so we want to find people more like them."	
Lack of insight into top of participation funnel	Expression of some breakdown in understanding of how the operational processes worked	"I have no idea." [Professor on how students are acquired]	
Corporate Partnerships – Limits of Platforms	Descriptions of the costs and benefits of working with external corporate actors	" It incorporates fantastically in blackboard not too much in edX."	Corporate Partnerships – Limits of Platforms
Financial Sustainability	Expression of need to ultimately put the products and program on a path to financial sustainability (break even)	"So my role initially was under digital acquisition, finding ways that we can increase conversion from people who register to credit convert."	Financial Sustainability
Cost Benefit Analysis	Descriptions of how to think through the bottom line of the program or product	"For a standard [MOOC program] course for the end of funnel, the furthest you can go is $600."	
Completion Rate Concerns	Expressed concerns about the low completion rate	"So, one of the challenges [host university] faced with edx.org is we have a lot of students but not a lot completing the classes and not a lot converting for credit."	Completion Rate Concerns
Goals	Explicit description of the goal of the program	"To keep retaining them and getting them to graduation."	
Content Difficulties	Descriptions of when students had difficult with MOOC content	"I would also say there is a technical part because you did mention that and there are things like detailed interactions — like say you're having a class in electrical engineering — we more and more are seeing deeper technical requirements — again that the faculty member isn't really built or trained to like know how to build a virtual reality, like you know electrical engineering lab, so they're going to need some technical resource support to like make sure that it integrates into the LMS platform and that this lab alone allows students to work appropriately and if those students are having a problem because they don't have the right laptop there's going to be some technical support requirements to to make these different tools work."	Content Difficulties
Cultural Sensitivities	Challenges described in producing culturally relevant content for a global audience	"It's just explaining to them that it is a global audience. That it is a little – one of the things that you have taken to account is dress, for example."	
Iterative Process	Examples of the producers describing how they adapted different versions of the course based on feedback or data or new goals	"So it is something that we're all striving for. We were calling it [MOOC program] 2.0 because now we are looking at, it's kind of funny, it's kind of like everything has got a version."	Future Aspirations
Future Aspiration	Descriptions of where the producers wanted to take the course in the future	"My boss is hitting up — my boss really likes the idea of these chat bots in online classes, you know. We're trying to secure funding — I don't know if it's come through yet — to do that over the summer is to start developing it."	
Data informed teaching	Examples of how the producers are using data to inform their building choices	"We will then have a cycle where we can use the outcomes of assessment to see which instructional resources are working to reach those objectives."	Evidence and Data Informed Teaching
Research on other MOOCs / Online Learning models	Producers reference other MOOCs and online learning examples they drew from	"So we went we went and looked at — I enrolled in like every online intro program that's available and looked at all of them and and so many of them are just lecture-project, lecture-project, lecture-project. It's so boring."	
Reflection on Pedagogy Gaps	Producers reflected on what worked and what did not	"But the first time, the first two times we made the class way too hard."	
Reflection on what did not work	Producers reflected on what worked and what did not	"And we don't teach that we just sort of throw them at problems and hope they learn as they go, which is kind of how we learned it, but that's probably not the best way."	
Assessment of MOOC overall	Descriptions of their assessment on the overall MOOC design	"Q: And do you think it's there?; A: No, no."	
Pathway Yields Better Outcomes	Description of a anecdotal data of promising outcomes from the MOOC pathway	"We're not at any statically significance yet, but those who do go through earned admission and then proceed onto [host university], their success in academic performance at [host university], whether on ground or online, is better than any incoming cohort at the university, whether first time crashing, basic transfer student at [host university]."	
Observed Student Challenges – Needs More Support	Descriptions of examples when the students needed more support.	"But then when we really think of where we want to put our efforts toward building new courses and really supporting students succeeding, it'll be on open EDX, where we can have a curated experience, we can do more interactive like interventions; we can have closer coaching, tutoring, whatever is needed we want to be able to make these students succeed."	Observed Student Challenges
Observed Student Challenges – Problem Solving	Descriptions of particular process based challenges that students faced - problem solving	"They're struggling with overall problem solving, like, how — if I have have these two pieces, and I have a problem, how do I could combine the pieces to help solve that problem?"	
Observed Student Challenges – Math Barrier	Descriptions of particular process based challenges that students faced - math barriers	"it's the C students that are on the edge that are a real challenge, because if you don't support them they could drop away, and if you provide — what what kind of level of support can I get, give them to make them a B student, to make them an A student, To sort of change their trajectory."	
Instinct to Collaborate	Examples of collaboration in the MOOC building process	"I can add you as — we can get you added as a beta-tester... and you can run through..."	Third Space Influence
Third-space Influence	Examples of third space producers exerting influence over the process	"At the same time, I'm also not a subject matter expert, so I am also putting trust in this faculty members who do teach daily to teach students. But also, like I said, as an advocate for the student feel I have to explain that to our faculty members; at times, remind them, okay this is not your typical random mill course. So, I think that's a conversation that we have often with our faculty members throughout the development process."	
Corporate Partnerships – Technology Providers	Examples of corporate partners providing technology employed in the course	"We integrate Cerego, Cerego is fantastic. I used that in several of my classes and that gives them another way to study and not realize their studying because it's a little bit interactive."	
Description of Collaboration with other Producers	Descriptions of collaborative process with other producers	"So, it's tough conversations like that. That you have to be just mindful of and I think they're so used to teaching for the students who are 18 to 23 or 18 to 30, That are in college. And so, I'm just trying to give them a little bit of perspective. So, it can be difficult."	Diffuse Processes
Diffused processes	Examples of how the various components of course design are diffused throughout an ecosystem, internal and external	"So we have some limited access to [corporate partner] analytics. They have their calendar in their platform. We have our calendar in our platform. And so when we take it from the [host university] ecosystem and put them into edX's ecosystem, because they are two different funnels, accounts, they don't talk to each other. So we all can... yeah, so we can't identify users going between both platforms."	
Development Processes	Description of the course development process	"So, but right now, the way it is is basically the faculty member works with the instructional designer to kind of lay out the course and build it. Then the instructional designer gets into the weeds and builds out the content."	
Differentiated Expertise	Description of different producers having different expertise	"So, we're putting these faculty members in roles that they may not have training in and doesn't necessarily support their true gift which is depth of knowledge in an understanding of mastery."	
Faculty Centric	Examples of when the faculty exerted control of the MOOC development process	"And it's not all of our classes, it goes back to the faculty because the macroeconomics my faculty, he's from Denmark. He is from a global location so he knows and he thinks about it globally."	
Description of Staff Role	Literal description of the tasks of the producers I met with.	"So, I do some things for [host university] online but I also have helped with as we migrated from the EDX platform to [host university]'s own hosted open EDX platform."	

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