A Framework for Considering the Matthew Effect in MOOCs: Hegemonic Design Bias

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Agenda

About me

Overview of my PhD

Definitions

Impetus of research

The Matthew Effect in MOOCs: Why?

Hegemonic Design Bias: Method, Explication, Implications

About me

- Head of Learning at Scale at Multiverse.io
- Visiting Scholar at Arizona State University
- Completed PhD at Cambridge in 2021, supported by Gates Cambridge
- Work is multi-methodological across educational theory, data mining, and design-based research
- And I stutter, just as an FYI

My PhD Work

- Meaney. (2021). Essays on the Design of Inclusive Learning in MOOCs, and Implications for Educational Futures. PhD Thesis. University of Cambridge.
    - **Meaney, M. (2023). Hegemonic Design Bias in Massive Open Online Courses (MOOCs): A Conceptual Framework Exploring Why MOOCs Struggle to Democratise Learning.**
    - Meaney, M., & Fikes, T. (2023). The promise of MOOCs revisited? Demographics of learners preparing for university. Journal of Learning Analytics, 10(1), 113-132.
    - Meaney, M. J. (2022, June). Designing and Building Inclusive, Entry-level Massive Open Online Courses (MOOCs): Perspectives from Producers. In Proceedings of the Ninth ACM Conference on Learning@ Scale (pp. 189-200).

Definitions

- **xMOOCS**: edX and Coursera style MOOCs, though potentially more broadly applicable (Liyanagunawardena et al., 2014)
- **Underrepresented**: Users without a tertiary education and/or from lower-socioeconomic background
- **Inclusive**: Learning experiences that meet the user requirements of an underrepresented population (Cambridge Inclusive Design Toolkit, 2021); whether and how the needs of users without a tertiary education, or from a lower SES background, have been considered in design

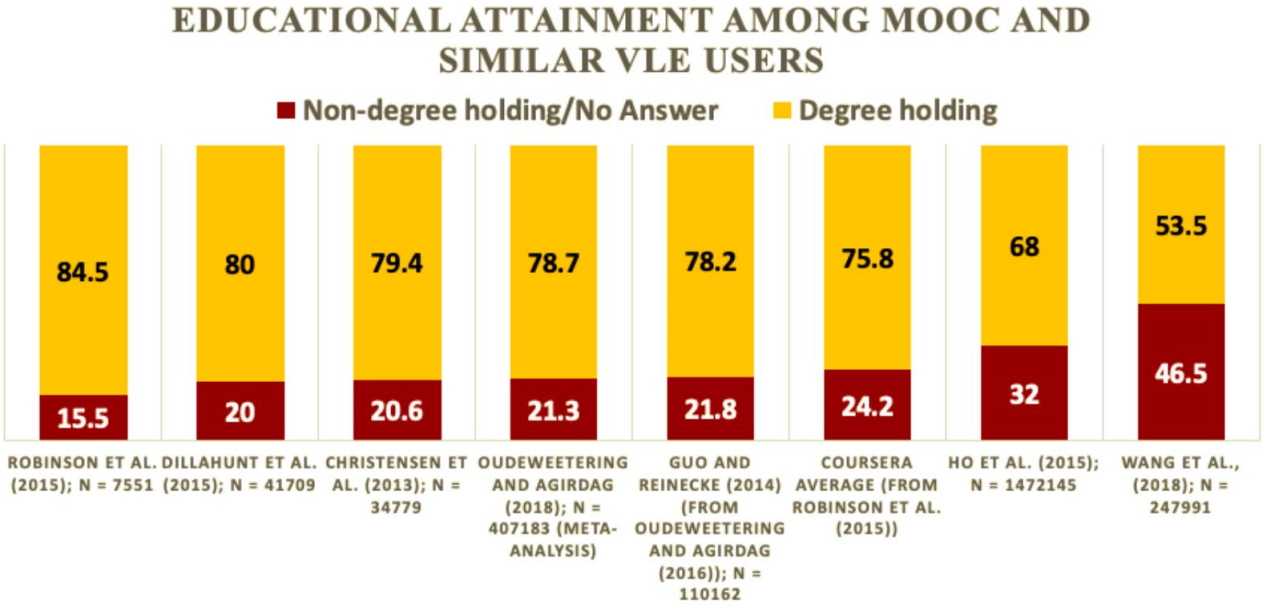
Impetus

“Moocs make education borderless, gender-blind, race-blind, class-blind and bank account-blind. Up to now, quality education – and in some cases, any higher education at all – has been the privilege of the few. Moocs have changed that. Anyone with an internet connection can have access.” (Agarwal, 2013)

“We envision a world where anyone, anywhere has the power to transform their lives through learning.” (Coursera, 2023)

“edX was founded by Harvard and MIT as an experiment to make the world’s best education available to everyone.” (edX, 2023)

Impetus



Gap between initial xMOOC discourse and empirical reality (Meaney and Fikes, 2019).

The Matthew Effect

Applied to the Sociology of Science originally by Merton (1961), whereby more senior researchers are more often cited, even if more junior researchers have similar quality work.

The Matthew Effect in Edtech

THE EDTECH MATTHEW EFFECT

FOR MANY YEARS, educators, designers, and policymakers have hoped that free and low-cost online technologies could bridge the chasm of opportunity that separates more and less affluent students. This dream has proven elusive.[1]

Reich, 2020

The Matthew Effect in MOOCs

- Description of empirical gaps between highly educated, high SES and other users, globally and within USA (Ruipérez-Valiente et al., 2022; Reich and Ruipérez-Valiente, 2019; Ganelin and Chuang, 2019; Hansen and Reich, 2015; Ho et al., 2014)
- Some exploration of heterogeneous engagement patterns between demographic subgroups of users (Kizilcec et al., 2020; Li and Baker, 2018; Kizilcec et al., 2017)
- Persistent call for better understanding why underrepresented users have struggled to enrol and complete (Goglio, 2022; Meaney, 2022; Gardner and Brooks, 2018; Joksimovic et al., 2018; Deng et al., 2017)

The Matthew Effect in MOOCs: Why?

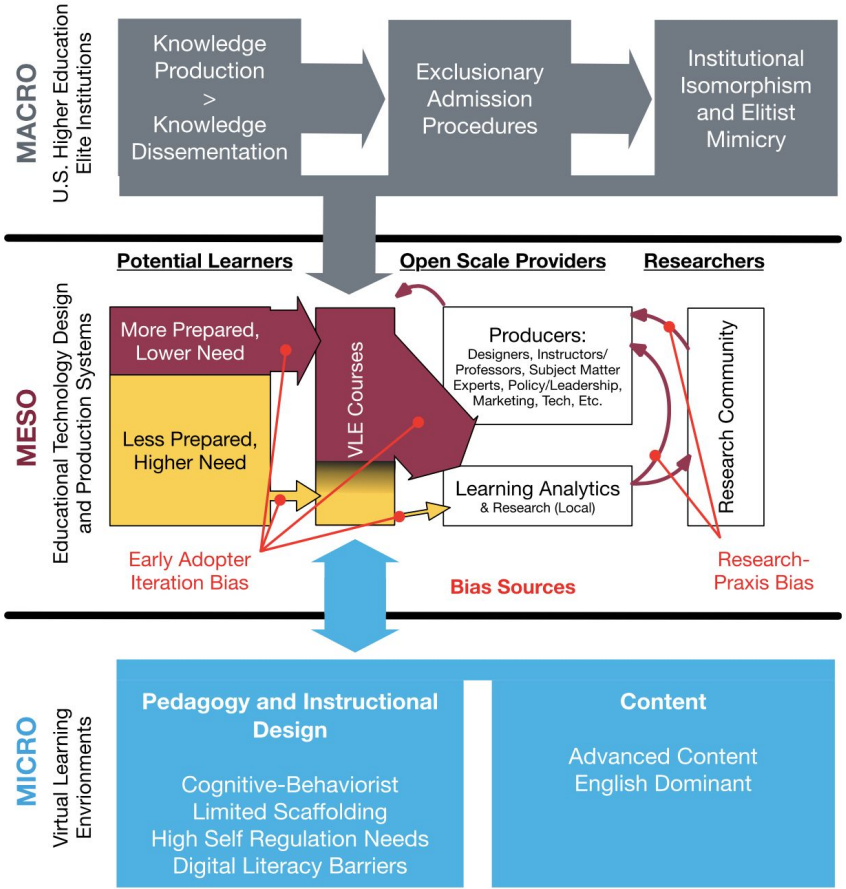
- **Overall**: Hypotheses are fragmented along disciplinary lines (Bozkurt et al., 2017; Raffaghelli et al., 2015; Ebben and Murphy, 2014)
- **Positivist**: Advances in data mining and machine learning develop precise models of learner motivation, behavior, and outcomes, often agnostic to questions of demographic differences or inclusion (Paquette et al., 2020; Gardner and Brooks, 2018; Joksimovic et al., 2018)
- **Critical**: xMOOCs embedded in a neoliberal (Adam, 2019; Jones, 2015); techno-optimist ideology that neglected traditional teaching and learning insights (Weller, 2014); did not adequately center the learner; and presumed, either through omission or commission, a widely attained autodidacticism in society (Knox, 2018; Knox, 2016)
- **Gap**: Lack of reciprocal engagement between theory and empirical work (Bozkurt et al., 2017), resulting in descriptions of reality, or complaints about it (Wegerif, 2013; 2019), and not theoretically coherent

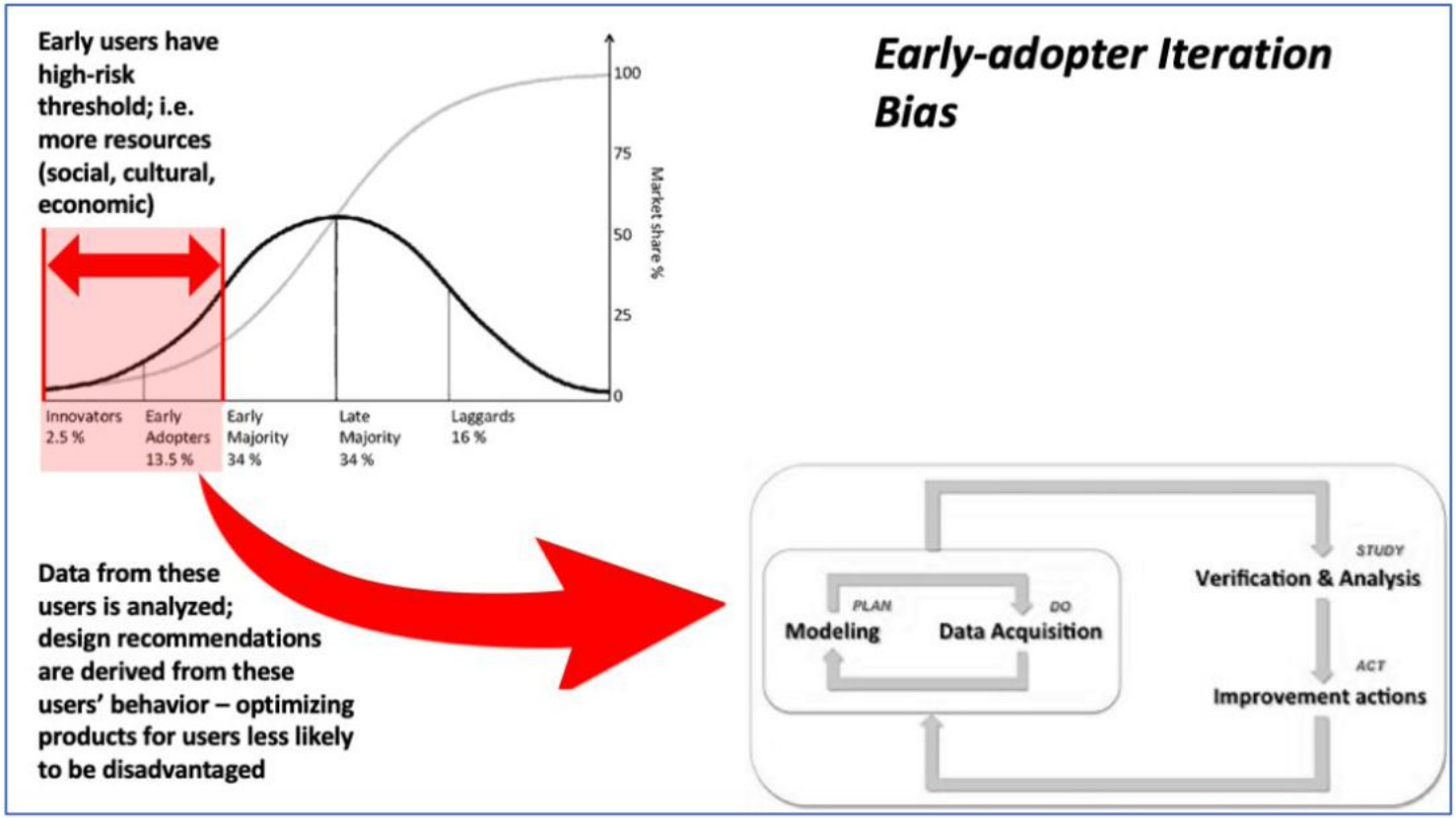
Method

- Theory-building exercise, yielding a conceptual framework to be further tested and iterated (Kettley, 2010)
- Critical synthesis of existing literature from a sociotechnical perspective emphasizing neither the social nor the technical (Meyer, 2006)
- Considers the Macro, Meso, and Micro level factors of MOOC production, based on levels of analysis for Distance Education more broadly (Zawacki-Richter, 2009)
- Critical yet constructive and operationalizable

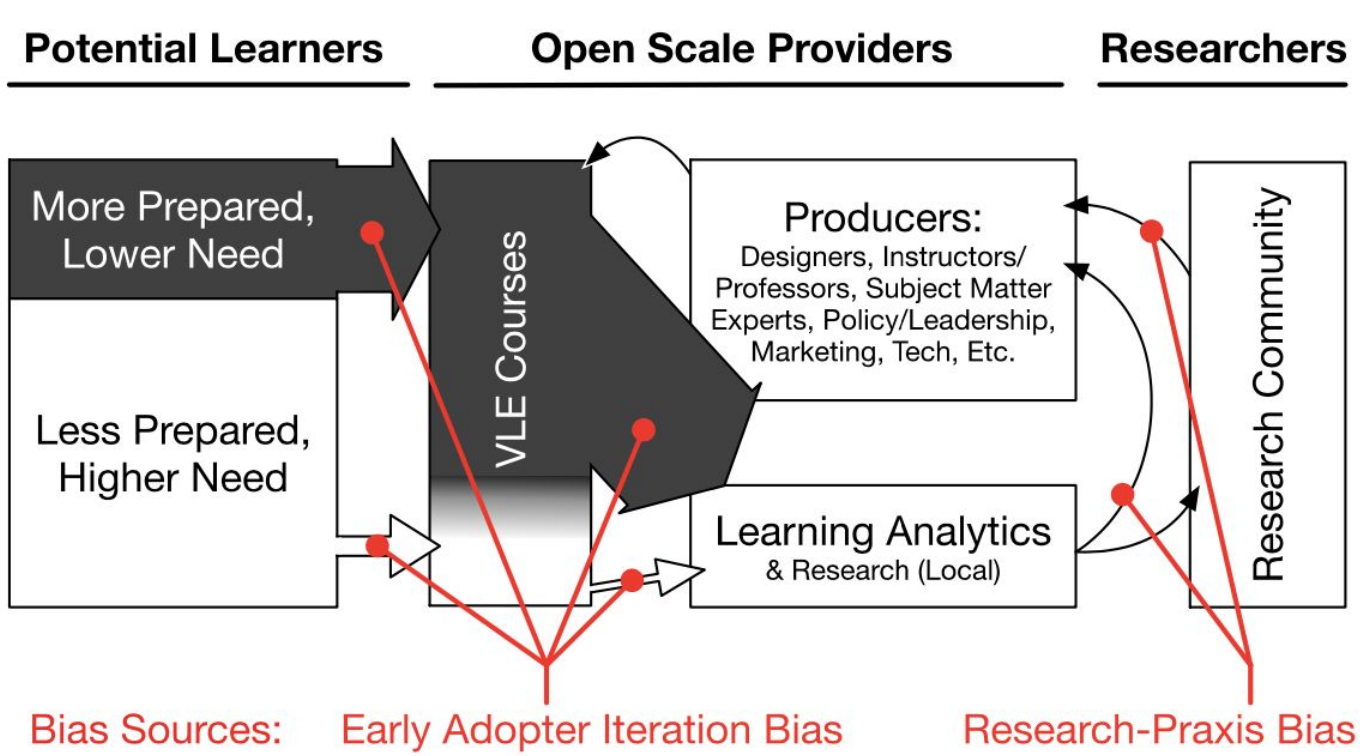
Hegemonic Design Bias. At the macro level, the relative importance of knowledge production compared to knowledge dissemination among elite institutions of higher education, the tendency for this focus to produce extremely exclusionary admissions standards, and elitist mimicry resulting in institutional isomorphism influence the design of MOOC Virtual Learning Environments (VLEs). At the meso level, a process termed 'early-adopter iteration bias,' whereby already educated users make up the majority of MOOC participants and produce the data that researchers and practitioners analyse 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.

Macro, meso, and micro level framework based on Zawacki-Richter, 2009.





Early-adopter iteration bias. 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: 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. From Meaney and Fikes, 2019.



The Meso Level of Hegemonic Design Bias: The Educational Technology Design and Production System. The universe of students who could benefit from VLEs contains a high proportion of less prepared, higher-need students. 'Early-adopter iteration bias' describes the situation in which courses designed for traditional higher education students lead students from more prepared, lower-need backgrounds to disproportionately enter VLEs and then succeed at higher rates. The data corpus produced by VLEs 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 VLEs receive insights from learning analytics and the research community that is driven by the more prepared, lower need majority, leading to innovation and optimization of VLE design that is even further away from the needs of less prepared, higher-need students. This is further complicated by the general disconnect between the research and practice communities. From Meaney and Fikes, 2019.

The Matthew Effect in MOOCs: What can we do?

MOOC market expected to grow 7x in the next five years. (Research and Markets, 2022)

The research we have is not the research we need. (Reeves and Lin, 2020)

- Macro-level
  - Elite universities could specify learners without a tertiary degree as their explicit audience in some MOOC courses, design for these learners, investigate outcomes and iterate. (Fit for purpose)
  - Non-elite colleges and universities, or alternative providers, which already demonstrate some capacity and ability to serve traditionally underrepresented learners, could be incentivized or funded to produce MOOCs for learners without a tertiary degree.

The Matthew Effect in MOOCs: What can we do?

- Meso-level:
  - Learning analytics could explore the specific behavior patterns of underrepresented learners in MOOCs with more explicit focus, and consider course optimization based on their behaviour patterns.
- Micro-level
  - MOOC instructional design could embed more practices aligned with the needs of non-tertiary educated learners
    - Connecting learning content to the real world for practical purposes, and for on the job relevance.
    - Developing courses that do not have advance math or reading comprehension as a prerequisite.

Future directions…to continue!

There is already significant work occurring across the Macro, Meso, and Micro levels that should be centered in the MOOCs research, and bridged to the mainstream MOOC providers.

Macro

- Non-mainstream MOOC providers, predominantly in Europe, attract more state-led support for specific educational outcomes, and have demonstrated a capacity to better serve underrepresented groups (Goglio 2022; Ruipérez-Valiente et al., 2022).

Meso

- Empirical work is beginning to focus on examining engagement patterns of demographically differentiated subgroups of learners (Meaney and Fikes, 2023; Sabnis et al., 2022; Williamson and Kizilcec, 2022; Nguyen et al, 2020).
- More qualitative work focused on research and practitioner communities through design-based research.

Micro

- Alternative MOOCs practices that are “Fit for purpose” for specific demographics of learners (Meaney, 2022; Reid and Barcena, 2021; King et al., 2014)

Conclusions and Limitations

- Hegemonic describes outcome not intent
- Operationalizable model with specific hypotheses to be tested
- USA, xMOOC centric
- More work is needed

The Matthew Effect is partially a design bias, and sometimes an explicit design choice.

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