

# Whose Experiences Do We Understand? Generalizability Considerations When Analyzing Data about Massive Open Online Courses

Karen D. Thompson  
Oregon State University

Sara Rutherford-Quach  
Stanford University

Claudia Rodriguez-Mojica  
Santa Clara University

Diego Román  
Southern Methodist University

Massive Open Online Courses (MOOCs) have generated considerable excitement and considerable skepticism since their recent inception (e.g., Kim, 2014; Perna et al., 2014). By fall 2015, approximately 35 million people had participated in 4200 courses offered by over 550 institutions (Shah, 2015). In addition to MOOCs' potential for expanding access to higher education offerings, scholars have touted their potential for facilitating research about online learning (Eichhorn & Matkin, 2016; Haywood, 2016). However, many questions remain about what participants are actually learning from MOOCs and how researchers can best make use of the huge amount of data the courses generate.

In Fall 2014, Oregon State University launched its first Massive Open Online Course (MOOC), [Supporting English Language Learners Under New Standards](#). Funded by the Oregon Department of Education and created in partnership with Stanford University, this course was designed to provide K-12 teachers with specific professional development on fostering English learners' skills in argumentation, a key practice emphasized in new education standards. As we have worked to understand what participants learned from this MOOC, we have encountered methodological issues that likely impact a wide variety of research on MOOCs. Specifically, because many participants in our MOOC began but did not complete the course, analyzing data collected at the end of the course provides information about a potentially non-representative sample of participants that likely does not generalize to the full group who started the course. After describing the generalizability issues that arose in our own research, we describe potential approaches for addressing these issues in MOOC research more broadly.

### **Generalizability Issues in Our MOOC Research**

To understand learning outcomes for participants in our course, we collected a variety of data at different time points. Participants completed pre- and post-course surveys. In addition to questions about demographics, motivation, and prior knowledge, these surveys included a direct assessment of learning. The course focused on

supporting K-12 students in constructing arguments, a key skill in new education standards (Stage, Asturias, Cheuk, Daro, & Hampton, 2013). Therefore, the assessment asked participants to evaluate a transcript of an argument made by a student and rank next steps they would take to further develop the student's skills in argumentation. During the MOOC itself, participants recorded their own students constructing arguments and used a rubric to analyze their students' argumentation skills. This enabled us to analyze changes in participants' ratings of a student argument before and after the course to see if participants' ratings shifted to more closely match those of experts. In addition to survey data, we also collected data through the course platform itself, including assignment completion and engagement with course content.

Given research showing positive effects of hybrid learning experiences that combine online learning with face-to-face interaction (U.S. Department of Education, 2010), the Oregon Department of Education provided grants to school districts, which districts could use to support teachers' engagement in the MOOC. Districts used these funds in a variety of ways, including providing stipends to teachers who participated, organizing in-person meetings to discuss course content, and providing release time for teachers to work on assignments. A key research question for our team was whether these support structures showed evidence of facilitating participants' learning. Therefore, in our pre- and post-course surveys, we asked Oregon teachers to indicate whether their districts were providing various supports (release time, stipend, district-provided facilitator, participating with a team of district colleagues, and/or other), and then we used participants' responses as variables in our analyses of completion rates and learning outcomes.

In Fall 2014 when the course was first offered, 5,102 people registered, 2,093 people completed the pre-course survey, 424 completed the first assignment, 269 completed the post-course survey, and 250 completed all course assignments. This pattern is consistent with the funnel of MOOC participation described by Clow (2013), with steep

drop-offs between each stage. In addition, the completion rate of 5% (250/5102) and the adjusted completion rate of 59% (the ratio of participants who completed the course to those who completed the first assignment, 250/424) is consistent with a large sample of Harvard and MIT MOOCs (Ho et al., 2014).

When we attempted to analyze the relationship between participants' outcomes and the types of supports they received, we noticed conflicting patterns that initially perplexed us. When using data from the pre-course survey and the course platform to analyze the relationship between types of supports participants received and completion rates, we found that Oregon teachers who reported receiving district supports, particularly those who received multiple types of support, were significantly more likely to complete the course than Oregon teachers not receiving any supports. For example, 74% of Oregon teachers who received

a stipend and release time completed the MOOC, compared to 30% of Oregon teachers who reported receiving no district support. (We discuss these findings more fully in other manuscripts.) However, when using data from the post-course survey to analyze the relationship between the types of supports participants received and a variety of learning outcomes (such as how knowledgeable they felt about argumentation, how prepared they felt to facilitate argumentation in their classroom, and how likely they were to change their teaching practices as a result of learnings from the course; see Table 1), we noticed the opposite pattern: Those not receiving any type of support reported more positive learning outcomes (i.e., those receiving no district support reported feeling more knowledgeable about argumentation, more prepared to facilitate argumentation in their classroom, more likely to change their teaching practices as a result of learning from the course, etc.).

Table 1. Responses to Questions about Learning Outcomes on the Post-Course Survey, by Whether Received Support from School District for MOOC Participations

Post-course Survey Question	Group Means	
	Received No Support	Received Support
How knowledgeable do you currently feel about supporting students in constructing arguments? (1=Not very knowledgeable; 5=Extremely knowledgeable)	3.45	3.38
How well prepared do you currently feel you are to set-up and facilitate argumentation (either oral argumentation or argument writing) in your/a real-life classroom? (1=Not very well prepared; 5=Extremely well prepared)	3.23	3.13
How satisfied are you with what you learned about supporting students in engaging in argumentation? (1=Very dissatisfied, 5=Very satisfied)	4.19	4.05
How prepared do you feel to change your instructional practice based on what you have learned? (1=Not at all prepared; 5=Extremely well prepared)	3.58*	3.17*
How knowledgeable do you feel about Oregon's new English Language Proficiency Standards? (1=Not very knowledgeable; 5=Extremely knowledgeable)	3.10	2.91
How comfortable do you feel aligning your practice to Oregon's new English Language Proficiency Standards? (1=Not very comfortable; 5=Extremely comfortable)	3.10	2.92
How knowledgeable do you feel about the Oregon English Language Proficiency Standard we focused on in this course: ELP Standard #4: An ELL can construct grade-appropriate oral and written claims and support them with reasoning and evidence. (1=Not very knowledgeable; 5=Extremely knowledgeable)	4.63	4.42
<i>N</i>	31	103

Note. Asterisks indicate when the difference between the group means is statistically significant. \*  $p < .05$

T-tests comparing means for those receiving and not receiving supports indicated that differences were usually not statistically significant due to relatively small sample sizes, as we will discuss below, but mean values for the participants receiving no supports were always higher than for those receiving supports, as shown in Table 1.

After our initial confusion, we realized one possible explanation for the conflicting patterns. When analyzing the relationship between types of supports and completion rates, our sample included all Oregon teachers who answered the pre-course survey question about types of supports their districts were providing ( $N=428$ ). We then merged data from the course platform to determine which of these participants had completed all course assignments. However, when analyzing the relationship between types of support and survey questions about learning outcomes, our sample was restricted to the Oregon teachers who completed the survey question about supports and also completed the *post-course* survey questions about learning outcomes ( $N=134$ ). In other words, in this analysis, we were only assessing learning outcomes for those who had completed the post-course survey, which was a substantially smaller group than had completed the pre-course survey. Prior research finds that those who complete MOOCs (without the types of external supports provided by districts) tend to be more motivated and have stronger self-regulation skills than non-completers (Kizilcec, Pérez-Sanagustín, & Maldonado, 2017). Thus, participants who completed the MOOC on their own without any type of district support, were likely different in substantive ways, potentially in ways that also correlated with the extent to which they might learn from the course, when compared to those who completed the MOOC with district support. Because we were comparing outcomes for groups who differed not only in whether they received district support but potentially also differed in their motivation and self-regulation skills, we needed to carefully consider what conclusions, if any, we could draw from this particular analysis.

## **Strategies for Addressing Generalizability Concerns in MOOC Research**

Many others have raised concerns and questions about MOOC research. For example, numerous scholars have urged their peers to move beyond a narrow focus on whether participants complete courses, noting that many people sign up for MOOCs with goals other than completion (Clow, 2013; Ho et al., 2014; Milligan, Littlejohn, & Margaryan, 2013). Scholars have also pushed for less emphasis on engagement and more emphasis on learning, encouraging their peers to focus less on participants' time interacting with course content and more on finding ways to understand how participants' procedural and conceptual understanding of course content evolves over time (Reich, 2015).

Numerous MOOC studies include caveats about the generalizability of their findings. For example, one widely-cited study concluded that participants' confidence, prior experience, and motivation impacted their level of engagement in the course but noted that their sample was limited to students still active midway through the course, when they invited individuals to participate in the study (Milligan et al., 2013). Another study analyzing predictors of retention and achievement in MOOCs also mentions the limitations of their sample (Greene, Oswald, & Pomerantz, 2015). The authors note that because only participants who completed the eight exams in the course (1,001 participants compared to 3,875 participants who completed the pre-course survey and 34,000 who signed up for the course) can be included in the achievement analysis, "the unique characteristics of this sample and likely restriction of range issues may have affected this analysis" (Greene et al., 2015, p. 947).

Generalizability is a perennial issue in research. As Holland (1986) explains, the population whose outcomes we would like to understand is not identical to the population whose outcomes we can actually study. Furthermore, given methodological considerations, the population for whom we can make causal inferences is an even smaller subset of the full population we seek to understand, even when using randomized experiments (Holland,

1986). In MOOC research, the dramatic reduction in sample size from the participants who sign up for a course to the participants who complete all assignments demands that researchers clearly describe the samples involved in each piece of their analysis and, by extension, the population to whom their conclusions may generalize.

Despite these generalizability concerns, there is still much that can be learned from MOOC research. By designing a robust set of data collection procedures, researchers can ensure that they have information about participants at various points throughout a course. This data might include: demographic information collected from the users' profiles on the course platform; pre-course surveys that include information about participants' goals for the course (Ho et al., 2014) and a pre-assessment addressing key concepts from the course (Reich, 2015); data about participants' interactions with course content; data from participants' assignment submissions; post-course surveys, including a post-assessment; and interviews with a cross-section of course participants, including individuals who did and did not complete the course. This rich variety of data would facilitate a range of analyses and a broader understanding of participants' experiences.

It remains impossible to analyze factors predicting course completion for participants who did not complete surveys providing data about the factors in question, just as it is impossible to analyze achievement results for individuals who did not complete the assignments that constitute the achievement variable. Nonetheless, by foregrounding generalizability concerns and by deliberately designing data collection in ways that explicitly address these concerns, we can move closer to understanding the experiences of MOOC participants.

### **Acknowledgements**

*Creation of the MOOC described here was funded by the Oregon Department of Education. Research on outcomes for MOOC participants is funded by an Oregon State University Ecampus Research Fellowship grant, for which Dr. Thompson is the PI. We thank Kenji Hakuta, Hsiaolin Hsieh, Lisa Zerkel, and Betsy Williams for their assistance during the MOOC itself and in assembling the data discussed here.*

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### Vision

The Ecampus Research Unit supports Oregon State University's mission and vision by conducting world-class research on online education that develops knowledge, serves our students and contributes to the economic, social, cultural and environmental progress of Oregonians, as well as national and international communities of teachers and learners.

### Mission

The Ecampus Research Unit (ECRU) makes research actionable through the creation of evidence-based resources related to effective online teaching, learning and program administration toward the fulfillment of the goals of Oregon State's mission. Specifically, the research unit conducts original research, creates and validates instruments, supports full-cycle assessment loops for internal programs, and provides resources to encourage faculty research and external grant applications related to online teaching and learning.

### Contact

Katie Linder, Ph.D.  
Director of Research  
Oregon State Ecampus  
541-737-4629  
[kathryn.linder@oregonstate.edu](mailto:kathryn.linder@oregonstate.edu)

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### Suggested Citation

Thompson, K. D., Rutherford-Quach, S., Rodriguez-Mojica, C., & Román, D. (2018). Whose experiences do we understand? Generalizability considerations when analyzing data about Massive Open Online Courses. *White Paper*. Corvallis, OR: Oregon State University Ecampus Research Unit.