Changing "Course": Reconceptualizing Educational Variables for Massive Open Online Courses

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In massive open online courses (MOOCs), low barriers to registration attract large numbers of students with diverse interests and backgrounds, and student use of course content is asynchronous and unconstrained. The authors argue that MOOC data are not only plentiful and different in kind but require reconceptualization—new educational variables or different interpretations of existing variables. The authors illustrate this by demonstrating the inadequacy or insufficiency of conventional interpretations of four variables for quantitative analysis and reporting: *enrollment, participation, curriculum*, and *achievement*. Drawing from 230 million clicks from 154,763 registrants for a prototypical MOOC offering in 2012, the authors present new approaches to describing and understanding user behavior in this emerging educational context.

Keywords: computers and learning; higher education; learning environments

Increases in the amount and kind of educational data offer researchers new opportunities to observe, analyze, and ultimately improve the learning process. As educational contexts change, however, the quantitative variables that we use to describe them can take on inertia. The uncritical application of old variables to new contexts risks irrelevant or inaccurate interpretations. In this article, we argue that massive open online courses (MOOCs) not only offer more and different data but also have different parameters as part of their character. MOOC data enable researchers to "zoom out" to analyze thousands of students as well as "zoom in" to analyze any single student trajectory in fine detail. This permits richer definitions of conventional educational variables and applications of conventional analyses at different scales. However, we further argue that the objects of analysis, whether large-scale or fine-grain, also differ from their brick-and-mortar analogs because of their context. We illustrate this by considering four conventional and widely used variables: *enrollment, participation, curriculum*, and *achievement*. Our thesis is that these variables must be redefined to be useful for description and evaluation of the educational experience in MOOCs.

We distinguish between redefining a variable by reoperationalization and redefining a variable by reconceptualization. Reoperationalizing a variable involves updating its operational definition while leaving its conventional interpretations and uses intact. Reconceptualizing a variable may involve updating its operational definition, but more importantly, it involves updating or differentiating its intended uses and interpretations, often to suit a new educational context. This framework is simple but sufficient to illustrate the opportunities presented by MOOC data; it draws on more comprehensive frameworks for validating variable uses and interpretations such as those by Kane (2006, 2013). We conclude by reflecting on nascent efforts to evaluate MOOCs, and we argue that these have largely involved reoperationalization and not reconceptualization of existing variables.

Motivating Redefinition of Educational Variables for MOOC Analyses

MOOCs are online learning environments that feature course-like experiences—for example, lectures, labs, discussions, and assessments—for little to no cost. In the academic year 2011–2012, professors at Stanford University and MIT launched courses that became the prototypes for the MOOC providers Coursera, Udacity, and edX (Pappano, 2012). We focus on these particular MOOCs, which are instructor-guided and designed to scale up to support large numbers of learners (Daniel, 2012). They also allow large-scale data collection in the form of tracking logs, discussion boards, and assessment results. We argue that these data are different from traditional classroom data not only in amount and kind but because of the context in which they are gathered. We list superficial and substantive differences between traditional classroom data and MOOC data here.

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Educational Researcher, Vol. XX No. X, pp. 1–11
DOI: 10.3102/0013189X14523038

First, the magnitude of data gathered is larger in terms of numbers of registrants per course, observations per registrant, and types of information. The numbers of registrants in these prototypical courses were each more than 100,000 (Johnson, 2012; Simon, 2012). Each interaction of the website users can be recorded—every click and text-based submission—resulting in large numbers of observations per user. Data can include submission times, IP addresses, and submitted text as well as context-specific data about the video, lab, discussion, or assessment for which the interaction was recorded. MOOC databases are therefore of a size and kind that is rare in brick-and-mortar classrooms.

Second, registrants are diverse in their intent or reason for registration as well as in their backgrounds, including age, schooling, and country of access (Breslow et al., 2013). Whereas residential classrooms conventionally restrict registration along some bounds useful for differentiating instruction (e.g., degree desired, age cohorts, or prerequisite knowledge), MOOC registration is unrestricted. The course presented as an example in this article included high school students as young as 15 as well as registrants over 70 (DeBoer, Stump, Seaton, & Breslow, 2013). There were registrants who had worked for years in the field as well as older registrants who were exploring the topic for the first time. Registrants accessed the course from 194 different countries (DeBoer et al., 2013). This diversity in background and intention is inconsistent with conventional interpretations of the word *student*. We argue that the concept of a "student" requires differentiation, which we demonstrate by challenging conventional definitions of traditional "student"-level variables. As we build to this argument, we use alternative terms for students, including *registrants* for those who register and *users* or *learners* for those who interact with the course.

Third, registrant use of course tools is asynchronous and relatively unrestricted in sequence. Evidence of this asynchronous use accumulates continuously in longitudinal databases. Every interaction with the server can be described using a subject-verb-object-time-location syntax. For example, a single observation might say, "user 56937 paused lecture video 13b at 5:48:30 PM on July 16, 2013, from IP address 194.158.64.0." Course materials, including lecture videos, discussion forums, and assessments, are not only optional but also accessible at different times, in different orders, and at different rates. These three features of MOOC data are neither mutually exclusive nor exhaustive, but they begin to demonstrate how and why conventional variables may be insufficient or inappropriate for MOOC analysis.

Redefining Educational Variables: Reoperationalization and Reconceptualization

The evolution of educational data and learning contexts often requires researchers to update definitions of educational variables. In this sense, the advent of MOOCs requires a recalibration similar to others that have occurred before, from informal learning environments (e.g., Bell, Lewenstein, Shouse, & Feder, 2009), to mobile learning and early massive classes (Mackness, Mak, & Williams, 2010), to the emergence of new online modes of interaction (e.g., Reich, Murnane, & Willett, 2012). Motivations for redefining variables include data availability, improved understanding of the educational context, changes to the political, social, or cultural environment, and changes to the use and interpretation of the variables. This perspective draws on modern validation frameworks (Kane, 2006, 2013): a variable's definition must align with the uses and interpretations it supports. Here, we distinguish between reoperationalization, or redefinition by changing the metric used in construction of the variable, and reconceptualization, or redefinition by changing the use and interpretation of the variable.

Reoperationalizing a variable involves using new data, new calculations, or new estimation procedures to bring the variable into alignment with its intended uses and interpretations. The recent evolution of the high school graduation rate is an example, as the graduation rate now has a standard definition at the federal level (U.S. Department of Education, 2012). This standard calculation was enabled by improved longitudinal data systems (Data Quality Campaign, 2010) and motivated in part by the increased use of high school graduation rates in school accountability systems (National Institute of Statistical Sciences/Education Statistics Services Institute, 2005). Here, the calculation of the variable was standardized to an adjusted 4-year cohort graduation rate to support well-established uses and interpretations.

In contrast, reconceptualizing a variable involves updating the way it is interpreted and used. These are theoretical rather than operational adjustments. Examples include the differentiation of curriculum to distinguish between intended, enacted, and assessed curricula (Porter, 2006), or the reframing of an achievement gap from a deficit to a debt (Ladson-Billings, 2006). Reconceptualization often motivates reoperationalization and may additionally require a change in the name of the variable or differentiation of the variable into subcomponents. In terms of psychological research, reconceptualization is akin to creating a new construct or differentiating an old construct.

Four Educational Variables in Conventional Courses and MOOCs

We illustrate the opportunities of MOOC data by demonstrating that four conventional educational variables—enrollment, participation, curriculum, and achievement—risk irrelevance in the MOOC context. Figure 1 creates caricatures of these variables in conventional classroom contexts (top half) and contrasts them with the same variables in the MOOC context (bottom half). We review each variable briefly here and discuss each in further depth in subsequent sections.

Enrollment is the number of students registered for a class by a selected reference date (Snyder, 1993; United Nations Education, Scientific, and Cultural Organization [UNESCO], 2012). Although "shopping periods" are common (Babad, Icekson, & Yelinek, 2008) and enrollment may be estimated at different points in time (Knapp, Kelly-Reid, & Ginder, 2013), enrollment is generally interpreted as the number of students committed to complete the full class experience (Hagedorn, Maxwell, Cypers, Moon, & Lester, 2007). In the top half of Figure 1, we illustrate the common reference date for registration at the beginning of the class with a triangle. In the bottom half of Figure 1, we illustrate that registration dates vary, and learner

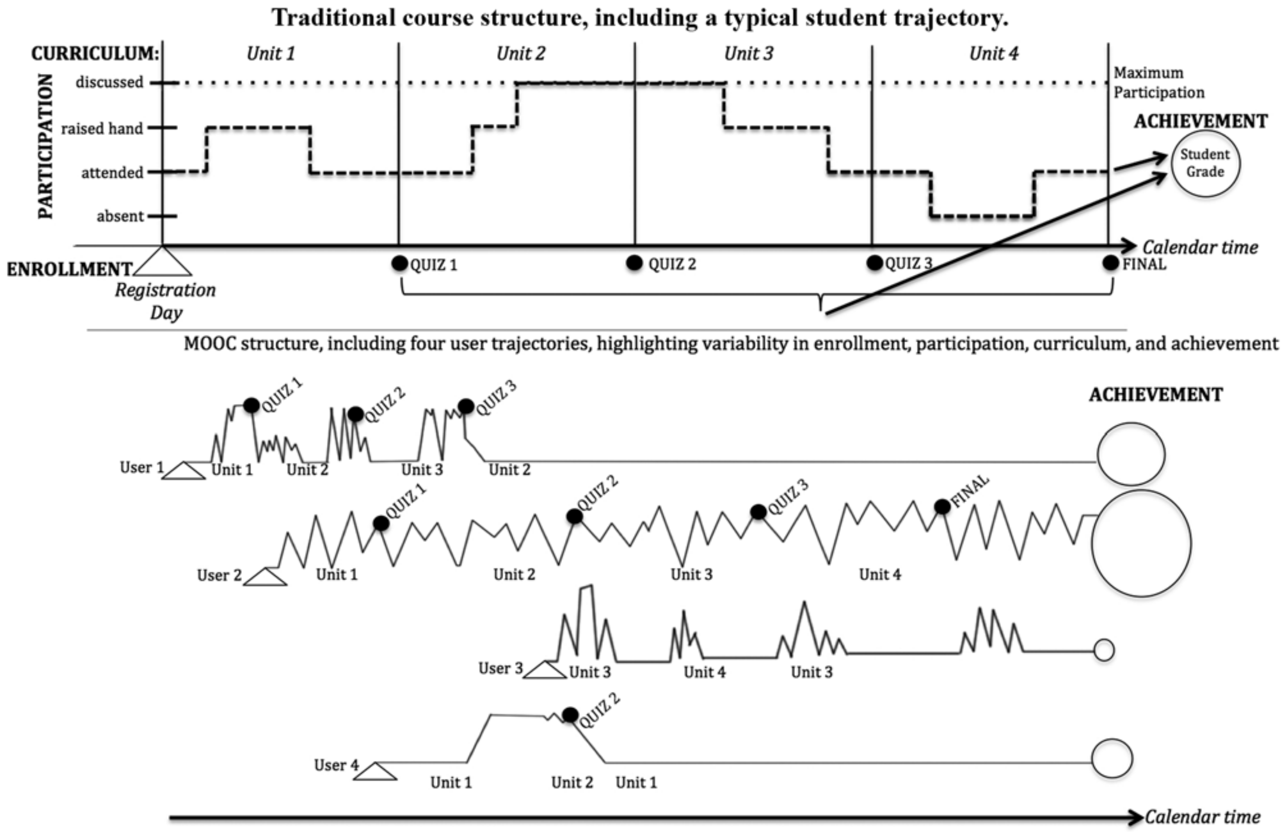


FIGURE 1. *Contrasting traditional course structure and variables. Top half: a traditional course structure and variables, including a typical student trajectory; bottom half: a massive open online course (MOOC) structure and variables*

behavior begins to suggest that users are neither accountable to nor interested in completing the full class experience.

Participation can be operationalized by attendance, a more passive measure of participation, or by metrics such as hand-raising or commenting, which are arguably more active (Astin, 1999; Gump, 2005; Crombie, Pyke, Silverthorn, Jones, & Piccinin, 2003; Hertenstein, Dallimore, & Platt, 2010; Fassinger, 1995; Randolph, 2007). Attendance measures are proxies for opportunity to learn, exposure to content, and time on task, even as attendance expectations and patterns in both residential and online classes are increasingly flexible (Adelman, 2004; Ashby, 2004; Hearn, 1988). Participation is incentivized by many grading schemes (Brookhart & Nitko, 2007) and measured as the quantity and quality of student contributions in class. The top half of Figure 1 provides a caricature of student participation on a scale from absent to active contribution, where the illustrated student happens to oscillate in participation over time. The bottom half of Figure 1 illustrates that the MOOC context allows participation to be more finely measured in time, along many possible metrics (a number of which we describe later), and with patterns that vary considerably across users.

Curriculum can be operationalized as either the sequential organization of class topics and activities, as exemplified in a course syllabus, or, more broadly, as the academic plan for a degree program (Lattuca & Stark, 2011). In this article, we focus on the curriculum as defined within a single course. Researchers recognize that the intended curriculum, as operationalized by syllabi, textbooks, lesson plans, or content standards, can differ from the enacted curriculum that is taught (Porter, 2006; Porter, McMaken, Hwang, & Yang, 2011). In the MOOC context, we begin to show that this distinction is less important than distinguishing available learning opportunities from those that learners choose to access, which researchers are now able to observe.

The top half of Figure 1 demonstrates the ordered pathway of a conventional course, where four units follow in a sequence and unit boundaries are common across students. The bottom half of Figure 1 begins to illustrate how MOOC users may select effectively individualized curricula, variable in the number of units, order of units, timing of units, and amount of time spent on each unit. Although these may vary in conventional classrooms as well, we demonstrate that the degree of asynchronicity—and our capacity to record it—is particularly striking in MOOCs.

Finally, achievement is often operationalized as a final course grade, usually a weighted average of student performance along a number of criteria (exams, papers, labs, and, in some cases, attendance and class participation) over the duration of the course (Brookhart & Nitko, 2007; Shepard, 2006). Achievement supports interpretations about student proficiency and effort with respect to the learning objectives of the course. Grading systems both incentivize and certify learning and proficiency. Some uses of achievement variables are student-focused and support interpretations about a student's learning or mastery. Others are instructor- or system-focused and support interpretations about the impact of the teacher and the course. Both interpretations assume that students participate actively in assessments and include demonstration of achievement as one of their goals.

The top half of Figure 1 shows assessments spaced at regular intervals at the end of each unit, where culminating achievement is a simple weighted average of assessment scores and participation. Although these same criteria can hold in the MOOC context, the bottom half of Figure 1 begins to illustrate that many users ignore assessments or take them at unpredictable times, resulting in achievement scores that are likely to be poor estimates of either mastery or the learning that has taken place. In the following sections, we provide real data examples that argue for the reoperationalization and, foremost, the reconceptualization of these four variables for the MOOC context.

Data

The following examples use real data from the first MOOC offered by MIT, "Circuits and Electronics," hereafter referred to by its abbreviated course listing, "6.002x." This course was the prototype for edX, the non-profit online learning enterprise founded by MIT and Harvard University. The course opened for registration on February 13, launched on March 4, and concluded on June 13, 2012. Online resources included videos, a discussion forum, a wiki, tutorials, and a textbook. Assessments were conducted in the form of embedded problems interspersed between online videos, as well as labs, homework assignments, a midterm exam, and a final exam. The final grade was calculated as a weighted percentage of correct answers on labs, homework, and exams, and learners scoring at or above 60% earned a certificate of completion in the course.

We do not intend this to be a full review of MOOC data structures or courses, and we consider 6.002x as a prototypical MOOC suitable for illustrating issues related to the definition of variables. As course designs and topics diversify and course tools proliferate, data may become richer, but we argue that the central challenges of variable definition that we raise here will remain. In the following sections, we illustrate these challenges by considering our four illustrative educational variables in turn.

Four MOOC Variables Reconceptualized

Enrollment

Enrollment in MOOCs is not limited to a single registration day or deadline. In 6.002x, registration was open 20 days before the launch of the class, and registration was possible up through the date the course officially closed. For nearly a third of the 6.002x registrants, the act of registration was their only interaction with the class—they never ultimately clicked on the class website. Although many presumably registered with the intent to complete the class, stated reasons for enrollment were diverse (Breslow et al., 2013).

Figure 2 shows considerable variation in registration dates. The majority of registrants signed up before the class launched, but Figure 2 makes it clear that registration occurred throughout the course, with small spikes after launch and the midterm. With no monetary cost to enter and no penalty for leaving, the entire

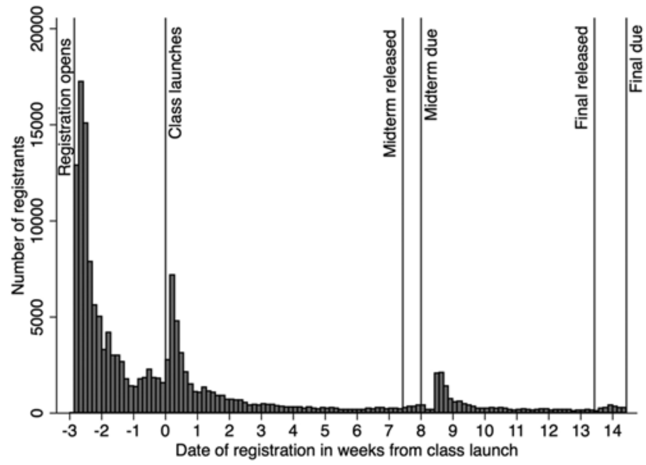


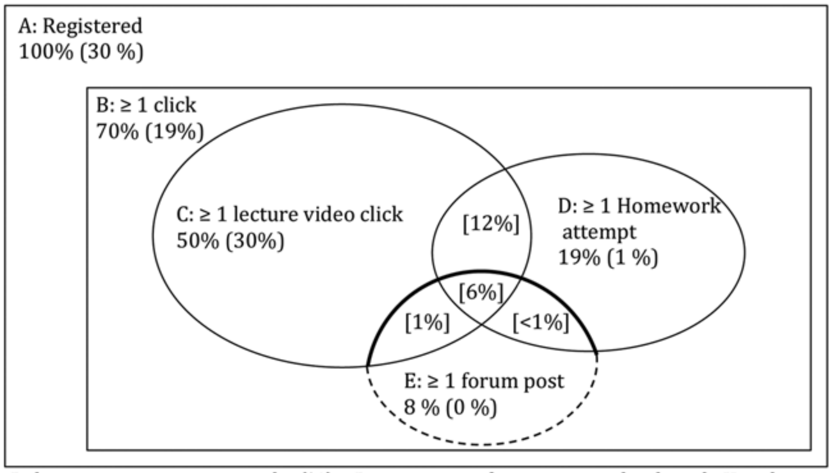
FIGURE 2. *Illustration of variation in course registration dates (*N = *154,763)*

14 weeks of the class could be considered as a "shopping period." There was no particular reason to officially withdraw one's name from the course registration list beyond avoiding course email updates.

As long as enrollments are unrestricted, with no selection mechanism based on commitment or intent, MOOC registrants will vary in preparation and goals far more than in traditional residential courses. Conventional course registration occurs in a structure that ensures that registrants will meet numerous preconditions. They are almost always students of a common institution that therefore share many characteristics and goals in common. They have further registered for a particular course, which itself incurs clear monetary and opportunity costs. An individual's decision to register is therefore more likely to reflect an informed commitment to complete the course, and the resulting group of enrolled students is likely to share many goals and background characteristics by virtue of their shared decision.

In contrast, the common MOOC policy of allowing anyone and everyone to register is not one that ensures common backgrounds or intentions among registrants. Figure 3 shows that of the 154,763 people who registered for 6.002x, 70% subsequently clicked at least once in the actual course; 50% clicked on a lecture video; 20% attempted a homework problem; and 8% posted in the discussion forum. If enrollment is interpreted as the number of people who make an informed commitment to complete a course, the number of total course registrations in a MOOC is a naïve operationalization at best.

Reoperationalizing the enrollment variable requires adjusting it to meet the conventional uses and interpretations that the enrollment variable supports. If we articulate this as "an informed commitment to complete the course," then this becomes the target parameter to estimate. However, enrollment statistics reported by both MOOC providers and the popular press are often the simple numbers of people who register—the largest and also most naïve estimate of this target parameter (e.g., Anders, 2013; Parr, 2013; Xu, 2013). These enrollment statistics are also the denominator for conventional attrition and completion statistics, raising the stakes on the definition. Researchers



Relative areas are not to scale. (%) – Percentages of registrants who do only X and not Y (or Z). [%] – Percentages of registrants who do X and Y (and Z).

Student Category (X)	Number Of Registrants that X	%	Number Of Registrants that Only X	%	Number Of X That Earn Certificates	%
A : Registered	154763	100	46908	30	7157	5
B : had ≥ 1 click	108008	70	29303	19	7157	7
C : had ≥ 1 lecture video click	77252	50	46398	30	7098	9
D : had ≥ 1 homework attempt	30034	19	1218	1	7134	24
E : had ≥ 1 discussion forum post	11999	8	0	0	4466	37
F: A∩B∩C∩D∩E	9286	6			4454	48

FIGURE 3. *Venn diagram and table showing contrasting operationalizations of enrollment counts and completion rates, across different criteria for minimum activity*

and MOOC providers have argued against the casual application of traditional enrollment/dropout statistics for MOOCs (e.g., Koller, Ng, Do, & Chen, 2013). However, if reoperationalization is the goal, what should the definition of enrollment and dropout be?

If "informed commitment to complete" were the intended interpretation of enrollment in MOOCs, this commitment could be determined by surveying registrants directly, by inferring it from the interactions recorded, or by creating structures, like a system for paid registration, that would increase the likelihood that registration reflects the desired interpretation. Figure 3 displays simplistic operationalizations if recorded interactions were used to infer this commitment. It also illustrates the challenges of employing this strategy. The center of the Venn diagram represents users who attempted at least one homework problem, posted at least once on the discussion forum, and clicked on at least one video. There are 9,286 of these users, and 4,454 of them earned a certificate, for a 48% completion rate. As the table shows, completion rates vary dramatically across even the most simplistic of alternative operationalizations of enrollment. And thousands of users completed besides these 4,454.

These data begin to suggest that although reoperationalizing enrollment is possible, the idea of enrollment may require reconceptualization for the MOOC context. The large number of users who clicked on videos but never attempted homework problems demonstrates that many registrants were not attempting to earn a certificate in the course at all. Restricting the definition of enrollment to the users who commit to course completion would neglect the activity and experiences of large numbers of users. Differentiating user enrollment by user commitment to particular pathways, for certification, auditing, or shopping, for example, allows for better description and analysis of the data in Figure 3. We advance this argument further in subsequent sections.

Participation

Figure 4 lists and compares 20 participation metrics to illustrate the potential of MOOC databases for describing the activities of learners. We select each metric to contrast with conventional operationalizations of class participation, from passive metrics like attendance to more active metrics like the frequency of contribution to discussions. We describe each metric in turn and then identify noteworthy patterns in the matrix of pairwise correlations. The three primary goals of this section are, therefore, to demonstrate that MOOC data allow for numerous and novel operationalizations of participation, to illustrate that pairwise associations between many of these metrics are low, particularly for certificate earners, and finally, to argue that this presents an opportunity to reconceptualize participation, similar to our reconceptualization of enrollment, along differentiated pathways created by individual students' goals or objectives.

The first four metrics in Figure 4 mimic conventional attendance metrics. The first two of these are the number of separate weeks (out of 14) or days (out of 102) that a learner appeared one or more times in the server logs. The third metric is the total

			General attendance				Clicks						Hours						Assessment			
			(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
General attendance	(1)	weeks		0.85	0.73	0.71	0.66	0.65	0.56	0.60	0.64	0.55	0.65	0.65	0.56	0.60	0.64	0.53	0.73	0.73	0.54	0.73
	(2)	days	0.59		0.83	0.81	0.76	0.73	0.61	0.59	0.69	0.58	0.75	0.73	0.62	0.59	0.69	0.57	0.72	0.70	0.48	0.71
	(3)	clicks	0.47	0.74		0.96	0.93	0.84	0.69	0.62	0.76	0.65	0.91	0.83	0.69	0.62	0.76	0.63	0.71	0.69	0.47	0.71
	(4)	hours	0.50	0.79	0.89		0.93	0.84	0.70	0.61	0.77	0.66	0.93	0.84	0.71	0.61	0.77	0.65	0.73	0.69	0.44	0.70
Clicks	(5)	lecture video	0.42	0.63	0.78	0.81		0.86	0.64	0.59	0.71	0.60	0.98	0.86	0.64	0.59	0.71	0.59	0.65	0.63	0.39	0.62
	(6)	lecture problem	0.40	0.64	0.76	0.80	0.73		0.60	0.58	0.69	0.56	0.86	1.00	0.60	0.57	0.69	0.54	0.67	0.66	0.43	0.65
	(7)	book	0.25	0.36	0.45	0.47	0.31	0.34		0.54	0.63	0.58	0.62	0.60	0.99	0.54	0.63	0.56	0.55	0.54	0.39	0.53
	(8)	tutorial	0.36	0.57	0.64	0.66	0.58	0.52	0.36		0.59	0.54	0.57	0.57	0.54	1.00	0.59	0.52	0.64	0.64	0.48	0.63
	(9)	discussion	0.34	0.56	0.64	0.65	0.40	0.44	0.35	0.49		0.67	0.69	0.69	0.63	0.59	0.99	0.64	0.65	0.64	0.46	0.64
	(10)	wiki	0.35	0.57	0.58	0.61	0.46	0.46	0.36	0.58	0.59		0.59	0.56	0.58	0.54	0.66	0.97	0.53	0.52	0.38	0.50
Hours	(11)	lecture video	0.43	0.65	0.74	0.84	0.92	0.73	0.30	0.55	0.38	0.42		0.86	0.62	0.57	0.69	0.57	0.63	0.61	0.38	0.60
	(12)	lecture problem	0.41	0.65	0.72	0.82	0.74	0.94	0.33	0.53	0.40	0.45	0.77		0.60	0.57	0.68	0.54	0.67	0.65	0.43	0.65
	(13)	book	0.27	0.39	0.46	0.50	0.33	0.35	0.96	0.37	0.36	0.37	0.34	0.36		0.54	0.63	0.56	0.55	0.54	0.39	0.53
	(14)	tutorial	0.37	0.58	0.63	0.68	0.58	0.53	0.36	0.97	0.49	0.57	0.58	0.55	0.38		0.59	0.52	0.64	0.64	0.48	0.62
	(15)	discussion	0.35	0.58	0.64	0.68	0.41	0.45	0.34	0.50	0.98	0.58	0.40	0.43	0.37	0.50		0.63	0.65	0.64	0.47	0.64
	(16)	wiki	0.33	0.54	0.54	0.59	0.43	0.43	0.33	0.53	0.55	0.91	0.40	0.44	0.35	0.53	0.56		0.51	0.50	0.37	0.48
Assessment	(17)	hw attempts	0.23	0.28	0.43	0.33	0.09	0.22	0.24	0.17	0.39	0.20	0.08	0.12	0.22	0.15	0.39	0.18		0.91	0.57	0.95
	(18)	lab attempts	0.26	0.32	0.47	0.39	0.17	0.27	0.25	0.21	0.44	0.24	0.16	0.17	0.24	0.20	0.44	0.22	0.78		0.60	0.89
	(19)	exam attempts	0.14	0.17	0.22	0.19	0.15	0.14	0.12	0.11	0.15	0.13	0.13	0.12	0.12	0.11	0.15	0.12	0.28	0.27		0.66
	(20)	grade	0.14	0.13	0.07	0.10	0.15	0.15	-0.02	0.09	-0.03	0.05	0.13	0.17	-0.01	0.09	-0.04	0.04	-0.10	-0.09	0.24	

FIGURE 4. *Twenty contrasting participation metrics and pairwise Spearman rank correlations for all clickers (upper triangle,* N = *108,008) and certificate earners (lower triangle,* N = *7,157)*

number of clicks, corresponding to each learner's number of separate interactions with the server. The fourth metric is an estimate of the total number of hours spent in the course. The time spent on a web page is notoriously difficult to measure in online environments (Clifton, 2012), let alone the amount of time that a user is actually attending to the content (Kelly & Teevan, 2003). We employ a very rough measure, taking the temporal space between two subsequent clicks and discarding times less than 10 seconds and greater than 30 minutes. (Correlations are generally robust across different standards for this "cutoff window" and do not threaten our illustrative point.)

Metrics 5 through 10 are click-based metrics for each course resource, and metrics 11 through 16 are time-based metrics for each course resource. The final four metrics relate to assessments. Metrics 17 and 18 are the number of attempts at homework and lab problems, respectively. The 6.002x instructors allowed unlimited resubmissions on homework and lab problems, to focus learners on formative rather than summative outcomes for these assessments (Mitros et al., 2013). Metric 19 is the number of attempts on the midterm and final exams, and metric 20 is the total grade, on a 0 to 100 percentage scale. Registrants scoring 60 and above earned a certificate of completion.

Figure 4 lists pairwise Spearman rank correlations for all 108,008 "clicking" users (see Figure 2) on the upper triangle and all 7,157 certificate earners on the lower triangle. All metrics exhibit modest to extreme amounts of positive skew on their reported scale, so we utilize rank-based correlations for more normative interpretations of similarity. These correlations help to address the question, Are learners with high ranks on one metric likely to have high ranks on another? Although correlations of count variables can be distorted when large numbers of users have zeros (Lambert, 1992; Mullahy, 1986), as is the case for some of these metrics, these correlations are not sensitive to a number of alternative specifications and again suffice to illustrate our points.

Figure 4 begins to illustrate diversity and individualization in patterns of MOOC resource use. Our primary observation is that pairwise correlations between metrics are low. Correlations on the upper triangle are higher and give stronger support to a single identifiable underlying dimension of "participation." Generally, however, spending time or clicks on a particular resource does not strongly predict spending time or clicks on other resources, for all users and particularly for completers.

Each metric in Figure 4 suggests a possible way to reoperationalize participation, from selecting one metric to forming composites of many. Instructors of MOOCs are able to measure attendance, participation, and online discussion in newly specific ways. However, the MOOC context motivates reconceptualization as well. Given that proportionally few MOOC registrants seem to be interested in achievement as measured by course grades, the conventional framing of participation as something that leads to (and is incentivized by) grades is less relevant than how and with what learners are participating. The low correlations in Figure 4 suggest considerable diversity in participation. We can see that students access the various parts of the course in very different ways, and we know that students come into this classroom from very diverse backgrounds. Some people watch videos. Others take assessments. The question may be less about whether this predicts course grades than about what invites and facilitates these patterns of participation. For some students, participation appears to be their primary goal. If researchers consider MOOCs less as courses than open invitations to engage with particular online resources, then participation patterns are less predictors of achievement than outcome variables in themselves.

Curriculum

The 6.002x syllabus was traditional in many ways: as an operationalization of curriculum, it presented topics arranged sequentially within ordered units, and assessment due dates were spread evenly through the 14 weeks of the course. Figure 5, however, extends our argument that users are operating outside of traditional assumptions by demonstrating unique student pathways

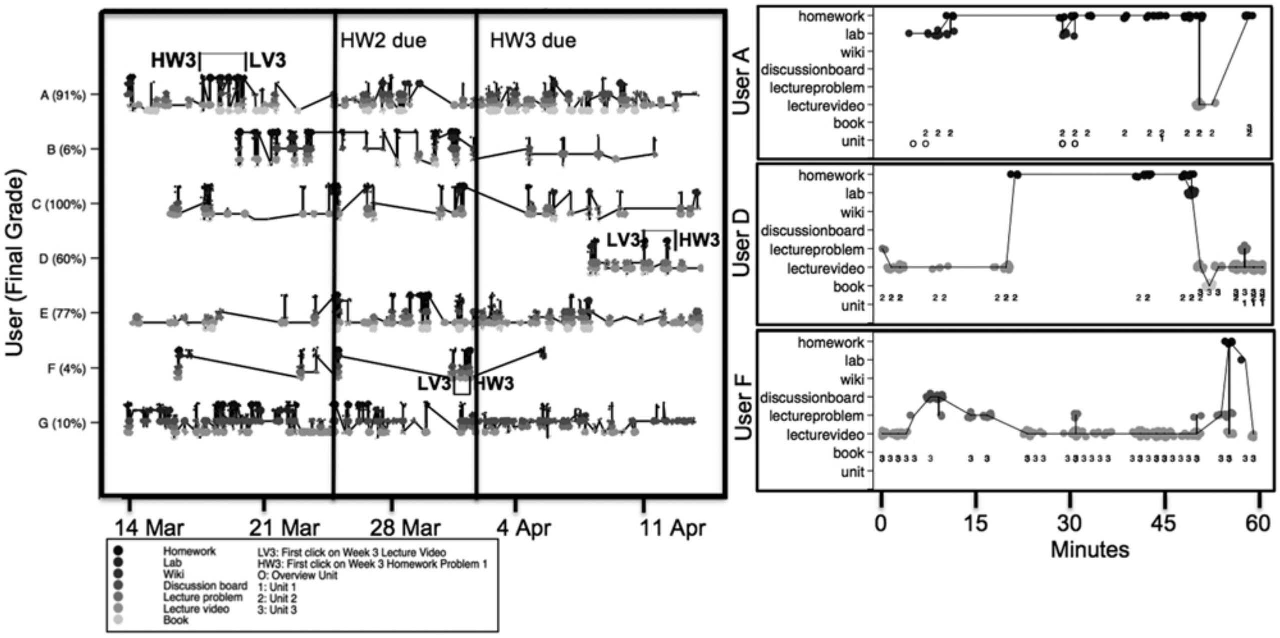


FIGURE 5. *Selected month-long (left) and hour-long (right) user activity plots by resource, with selected homework and lecture video interactions (left) and unit interactions (right) noted*

through units and assessments. It therefore suggests that curriculum should be both reoperationalized and reconceptualized.

In Figure 5, we illustrate variability in the curriculum as users chose to navigate it. On the left-hand side of the figure, we show a "storyboard" of the click-stream activity of seven selected users over a month-long period. We selected these users from those who viewed the first lecture video of unit 3 (a topic at a time when course registrations were more stable) who also attempted the first homework problem in unit 3. We use these two events to illustrate an expected, conventional trajectory for a student in a residential class. We further restrict the sample to users whose first interactions with these two activities occurred within 2 days of one another, and from this subsample, we selected seven contrasting illustrative users. These sequences illustrate the diversity and asynchronicity of learner use of course materials and, we argue, encourage new perspectives on the idea of curriculum.

The users are labeled A–G in the section on the left, and each point in the sequence associated with each user represents an interaction with a particular resource (identified by the legend) at a particular time in a 1-month period. Within each student's sequence of activities, the resources are organized on a vertical axis, with arguably less interactive resources, like the e-textbook and lecture videos, lower on the axis and arguably more interactive resources, like wikis and homework submissions, higher on the axis. The vertical axis is largely arbitrary, and clear distinction of the points on the axis is not particularly important. The graphic allows spikes in the sequence to be interpreted loosely as a period in which a learner uses more and less interactive resources in close succession. Lines without points represent periods of inactivity between course interactions. The figure illustrates that learners differ in both the resources they use and the sequence and frequencies at which they use them.

Figure 5 displays the due dates for the second and third homework as dark vertical lines. For three of the users, we show their first viewing of the lecture video (LV3) and their first viewing of the homework (HW3). User F accessed the content and then the homework just before the due date, in line with conventional expectations about students in a predictable curriculum. User A accessed the content and related homework problem well before homework no. 3 was due—before homework no. 2 was due, in fact—and accessed the homework before ever watching the related lecture video. User D accessed the content and the homework after the due date, even though doing so meant User D would not receive credit for that homework toward a certificate of completion.

On the right-hand side of Figure 5, we select an hour within the pathways of each of these three users that illustrates their activity in greater detail. We show resource use as well as the "units" of content to which they correspond. Whereas Figure 4 showed differences in the degree to which users interacted with resources, Figure 5 illustrates differences in the sequence and patterns of their use. The level of detail with which we can analyze these pathways allows us to reoperationalize curriculum as a summary of what users actually do. One major difference between the intended curriculum and the experienced curriculum is that the latter can be more difficult to measure (Martone and Sireci, 2009). Figure 5 therefore reveals the rich opportunities for new operationalizations that are present in MOOCs.

These illustrations also motivate reconceptualization of curriculum, not as standard content at standard times, or even summaries of what users do, but as individualized pathways motivated by individualized objectives for the learning experience. The instructor's assumption of curriculum as the prescribed set of materials and order in which students complete activities may be misguided in residential classes, but this may be a particularly misleading assumption in MOOCs. In MOOCs, learners can generally ignore or override an instructor's decision about the sequence in which course material is covered. Admittedly, some residential classes may be more flexible in allowing or encouraging students to read, watch videos, and work ahead of schedule. Also, in MOOCs, weekly material may be released and constrained along a certain schedule. However, the data clearly illustrate that MOOC participants, given broad access to different course materials and units, demonstrate asynchronicity in various ways that are unlikely to be possible, let alone recorded and researched, in residential classes.

The MOOC space is already allowing instructors to incorporate individualized pathways into their intended courses at a broad level, for example, allowing students to designate as "auditors" or "enrollees" (edX, 2013). This can occur either by passively allowing asynchronous interaction or by designing intentional "choose your own adventure" pathways. Our illustrations are a reminder that the curriculum that MOOC learners enact for themselves will always be more individualized still, because individuals may take advantage of or ignore affordances of any intended course structure as they see fit. This flexibility offers an opportunity for a data-driven feedback loop, where learners take advantage of individualized curricular supports and instructional designers take advantage of learners' unpredictable use of these supports in order to advance their designs (e.g., Bacow, Bowen, Guthrie, Lack, & Long, 2012; Jih, 1996).

Achievement

Final grades in 6.002x were weighted averages of assessment scores. This conventional operationalization of classroom achievement was included in Figure 4 (Metric 20) and Figure 5 (for each user, in parentheses). In Figure 6, we demonstrate patterns in MOOC achievement data that are unfamiliar in conventional contexts, to motivate reoperationalization and reconceptualization of achievement for the MOOC context. The figure is a pairwise scatterplot of the 108,008 "clickers." The scatterplot underlies one of the correlations in Figure 4 that contrasts the operational course grading scale (Metric 20) with the integer number of separate days that users interacted with course content (Metric 2). Other pairwise relationships shown in Figure 4 could be explored in similar scatterplots. Points have been jittered to visualize the disproportionate density in the lower left-hand corner. The horizontal line distinguishes the 7,157 certificate earners (on or above the line) from those who did not earn certificates.

The conditional average grade is shown as a solid line in Figure 6. Unsurprisingly, users who visit the course more frequently receive higher grades on average. Many reoperationalizations of achievement are possible, from simplistic partial-credit policies that penalize initially incorrect answers to more elegant solutions using item-response modeling techniques (e.g., Wise & DeMars, 2006). These models may also be able to capture learning as it is happening, as students get initial answers incorrect and proceed to correct answers with feedback. Courses may also explicitly incentivize different elements of participation as achievement by counting these in the calculation of the final

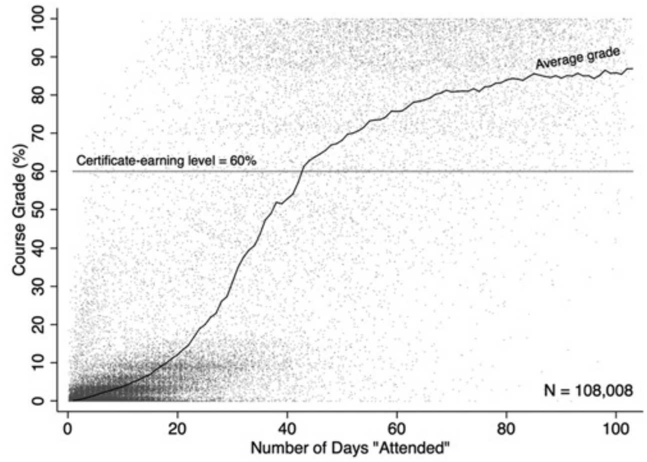


FIGURE 6. *Individual course grades plotted against individual days "attended" (>0)*

grade for certification. This could include ungraded problems that resemble conventional assessments, like lecture problems, or attendance-like metrics akin to those in Figure 4. As the intended uses of MOOC certificates are still unarticulated, assessment purposes can be formative and focused on leading students to correct answers.

Figure 6 also reveals groups of students who seem to have different motivations for taking the course. Consider the conditional distribution of grades when the number of days "attended" is 20, 40, or 60. In light gray, near the horizontal axis of the graph, a small but noticeable number of users can be seen to have 0% correct. Although it is possible that these users have learned nothing, we find it far more plausible—and hardly surprising given the openness of MOOCs—that these users have very little interest in the assessment component of the course, let alone certification. At the same time, they are clearly making frequent visits, in some cases more than four times a week. Inclusion of other participation metrics from Figure 4 (e.g., clicks, hours spent on lecture videos), as variables for the horizontal axis of Figure 6 reveals similar numbers of these kinds of users. Like User G in Figure 5, these users seem less likely to be students than "auditors," as that term commonly describes students who participate in a class but do not complete graded assessments or receive credit.

As we argued in earlier sections, conventional interpretations of enrollment usually assume that students have made an informed commitment to complete a course. This unwritten contract is neither offered nor signed in a MOOC. Without such a contract, any user below the pass line could have failed to master course material or, just as plausibly, had mastered it but was never interested in demonstrating that accomplishment. In order for operationalizations of achievement to meet the assumptions required for conventional use and interpretation, at the very least, interpretations should be restricted to only those users who can be identified as having committed to complete the course.

A simple way to reconceptualize achievement is to differentiate the variable by intention that can be inferred from activity. An ad hoc but transparent approach involves carving the bivariate scatterplot in Figure 6 into categories. Noncompleters who attend 5 or fewer days are "shoppers" (77,453, or 72% of clickers). Noncompleters who attend 6 to 15 days are "dabblers" (14,968, or 14% of clickers). Noncompleters who attend 16 days or more are "auditors" (8,430, or 8% of clickers). This is a simple approach for which many more advanced alternatives are possible (e.g., Kizilcec, Piech, & Schneider, 2013). We may infer that these students have different goals for their achievement, and we may set individualized and differentiated achievement expectations accordingly.

Individualizing and differentiating definitions of variables in this manner is not helpful for many purposes. If we were to conduct a formal evaluation of MOOCs, defining achievement in terms of intention while defining intention by action simply results in auditors achieving auditing, shoppers achieving shopping, and dabblers achieving dabbling. It may be interesting to understand variation in user activity, but it is not helpful to "discover" that the completion rate of completers is 100%. Criteria for evaluating MOOCs are nascent, and reoperationalization of conventional variables, particularly outcome variables like achievement, may need to suffice for restricted purposes like program evaluation, at least until new outcome variables are developed.

As an alternative, students could set and pursue individualized goals that represent criteria for evaluating their course experience, in line with the framework proposed for gamification in education (e.g., Lee & Hammer, 2011). Individualization by user intention reconceptualizes achievement as the accomplishment of self-defined goals rather than criteria set by instructors. This would require additional information from users to define these goals, as well as development of the platform to reflect individual progress toward achieving these targets.

Discussion

The massive databases of MOOCs hold immense analytic potential but are ripe for misuse and misinterpretation. It is not only the magnitude of data, but also the diversity of user intentions and backgrounds and the unconstrained asynchronicity of their activities that distinguish the MOOC context from conventional classrooms. As we have argued, although the data allow for reoperationalization of conventional variables, the MOOC context demands more than repackaging new data into old variables. Reconceptualization of these variables toward differentiated and individualized interpretations of enrollment, participation, curriculum, and achievement is necessary to capture the variation in user intention and action that we have illustrated in our figures.

The empirical snapshots included in this article were taken at the dawn of this new educational context, in the first year that large-scale MOOCs were launched. This time may prove to be particularly volatile, but we argue that it is also likely to surface the most essential complexities. We do not intend this as a comprehensive review as much as insight into MOOC origins, and we anticipate that conventional variables may be challenged in many other ways as MOOCs continue to evolve. In our review of MOOC variables, we find that those supporting common metrics for course evaluation, including dropout rates and certification numbers, are particularly problematic. Low barriers to registration and unconstrained, asynchronous course use both allow and encourage diversity in registrant intentions and actions. Interpreting enrollment and achievement variables conventionally, no matter what the reoperationalization, seems likely to result in criteria that miss the point.

Although MOOC students in a given class vary more in age, educational attainment, and geography than conventional students in a college setting, early results suggest that their average age and educational attainment is higher than traditional college students or even traditional online programs (Breslow et al., 2013; Fowler, 2013). In our paper, we describe diversity in terms of the high degree of variability among registrants on numerous measurable dimensions, and we argue that this motivated reconceptualizing "student"-level variables. We also recognize that MOOC instructors and providers can address diversity in terms of the characteristics of the populations that they may aspire to reach. Differentiating and reconceptualizing "student" both embraces the diversity we see in the data and offers an opportunity to target more—or more specific—audiences.

One application that we have not addressed directly is the use of MOOCs for course credit in existing institutions of higher education. This is an area of active debate, as lawmakers and administrators weigh how and whether to grant credit for these courses (Kolowich, 2013; Young, 2012). In a replacement model, where students enroll in a MOOC instead of a residential course, the variability of users and the asynchronicity of their activities are likely to be restricted by conventional institutional structures. Reconceptualization of conventional variables might be less necessary or less dramatic, with formal enrollment ensuring more similar intentions among students. Definitions of participation, curriculum, and achievement could be reoperationalized but would likely serve conventional purposes. The richness of MOOC data would certainly enable new and worthwhile opportunities to understand online learning, but the context would not necessarily require reconceptualization of conventional variables.

As MOOC offerings continue to proliferate, we intend our arguments to discourage knee-jerk analyses of their data that neglect the magnitude, diversity, and asynchronicity of this new data context. Each of our examples has illustrated registrant-to-registrant variability in MOOC use. Enrollments occur at different times and for different reasons. Different participation metrics have low correlations across resources. User interaction with curricular resources happens at different times, in different sequences, and at different rates. In addition, conventional measures of achievement seem to be disconnected from what many users intend to achieve. As a result, we recommend a general reconceptualization of these variables in terms of individualized and informed user intentions.

These intentions can be estimated both by collecting new data and by mining existing data. Instructors and researchers can gauge the backgrounds and individual goals of users who register for MOOCs with surveys and pretests. In parallel, analysis and mining of log files to identify the actions users are taking, along the lines that we have demonstrated, may also surface the intentions of the students. Targeted surveying with common variables, controlled experimental designs, and thoughtful secondary data analysis are all necessary to advance our understanding of MOOCs. Meanwhile, MOOC platforms continue to develop, in particular to allow recognition of and adaptation to the unique needs and goals of individual users (e.g., the currently open HarvardX course "Unlocking the Immunity to Change" HarvardX course; Kegan & Lahey, 2013). With these developments, course designers and instructors already seem well aware of the diverse audience and opportunities in the MOOC context. We argue that data analysis and interpretations of variables must follow suit.

In this article, we show that enrollment, traditionally measured as the number of students registered as a proxy for students who commit to complete a class, can be reconceptualized as differentiated tracts reflecting users' individual goals. Participation can be reconceptualized according to the diverse ways it occurs and could be an outcome in its own right. Curriculum can be reconceptualized as individual, asynchronous pathways, for which there is no correct, prescribed way to proceed. Finally, achievement can be reconceptualized relevant to individual goals. Educational researchers must critically examine the assumptions and desired interpretations of traditional concepts in the MOOC space; we demonstrate a framework that can be built on and extended in future analyses.

NOTE

This material is based on work supported by the National Science Foundation Division of Research on Learning in Formal and Informal Settings under Grant 1258448. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the National Science Foundation. The authors are also grateful for the support of the MIT RELATE group, edX, and the 6.002x course team. The authors would also like to thank four anonymous reviewers, two of whom inspired some of the language in this introduction, including "different parameters as part of their character" and the "zooming" metaphor.

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Manuscript received September 10, 2013
Revision received December 2, 2013
Accepted January 14, 2014