DROPOUT RATES, STUDENT MOMENTUM, AND COURSE WALLS: A NEW TOOL FOR DISTANCE EDUCATION DESIGNERS

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ABSTRACT

This paper explores a new tool for instructional designers. By calculating and graphing the Student Momentum Indicator (M) for 196 university-level online courses and by employing the constant comparative method within the grounded theory framework, eight distinct graph shapes emerged as meaningful categories of dropout behavior. Several of the graph shapes identified Course Walls, that is, areas of the course's lesson sequence wherein the student's momentum to finish the course is significantly slowed or halted. We posit that instructional designers can apply the evaluation of Course Walls to course revisions to reduce dropout rates.

Keywords: Dropout rates, student attrition, student persistence, student momentum, course walls, instructional design, distance education

INTRODUCTION

At any given time, millions of students are enrolled in distance education courses. During the fall of 2014, 5.8 million students were taking courses at a distance (Allen, Seaman, Poulin, & Straut, 2016). Too many of these students enroll in courses, pay the required tuition, and subsequently drop out. Some even do a portion of the required course work before ultimately dropping out. Estimates of dropout rates are 10% to 20% higher than their face-to-face counterparts (Bart, 2012). Others show the dropout rate to be six or seven times higher in online courses when compared to face-to-face courses (Patterson & McFadden, 2009). While the real causes of student attrition are complex, it is safe to say that the online dropout rate exceeds that of the traditional educational environment (Waugh & Su-Searle, 2014).

Boton and Gregory (2015) discussed elements of "culture, motivation, learning management systems (LMS) and online pedagogy" as factors that influenced online dropout rates. According to Gaytan (2015), the faculty rated student self-discipline as the most important factor affecting online dropout rates and the students pointed to the level of faculty interaction and meaningful feedback as factors that influenced their decision to drop out of a course. Others considered student demographics such as gender, race, and age as well as other student characteristics like GPA, financial aid, GMAT scores, and online course withdrawal history as predictive factors related to online dropout rates (Cochran, Campbell, Baker, & Leeds, 2014; Patterson & McFadden, 2009). Still others describe factors related to students' experiences before enrollment and while enrolled that influence online dropout rates (Rovai, 2003).

To complicate the discussion further, a universally accepted definition of a dropout does not exist and course dropout rates should not be compared across organizations because of differences in reporting (Atchley, Wingenbach, & Akers, 2013). For example, under one definition of a course dropout, a student has to be active in the course during the first three weeks (Bälter, Cleveland-Innes, Pettersson, Scheja, & Svedin, 2013). Alternatively, Frydenberg

(2007) defines a dropout four ways: as a student who registered but dropped prior to class start, prior to the start of instruction, during orientation week, or after orientation week. Also, Levy (2007) defined a dropout in his study as a student who voluntarily withdrew from e-learning while acquiring financial penalties.

DESIGN

We chose to study dropouts within single enrollment online education courses as opposed to an online diploma/degree program. As a result, we chose to define dropout as a student who enrolled in an online course, paid the requisite tuition, and completed at least one course lesson before dropping out. This definition eliminated from the dropout calculation any nonstarters: students who enrolled and withdrew without doing any work. We decided that a student who enrolled and then withdrew without doing any work was not engaged enough in the course to be considered a dropout for instructional design purposes.

According to Lee and Choi (2011), well-designed courses decrease student dropout rates in the online environment. But, what tools do instructional designers have related to designing a course with dropout rates in mind? An extensive literature review yielded no tools worth considering for instructional designers with regards to decreasing dropout rates.

The literature indicates that at the program and course level instructional design does have an effect on student persistence (Aragon & Johnson, 2008; Burns, 2013; Creelman & Reneland-Forsman, 2013). When considering course design as a cause of student attrition at a more granular level, such as each module or lesson within a course, there is a paucity of literature. Analyzing large data sets in an effort to increase student learning, support decision-making, and improve program and course administration is becoming more popular in educational settings (Brown, 2011; Christensen, Howell, & Christensen, 2015; Fritz, 2011; Shum & Ferguson, 2012). By examining student attrition on a lesson-by-lesson basis, a new tool for improving course dropout rates, to be utilized by course designers, can be developed. This tool will enable designers to pinpoint specific areas within a course where the highest rates of attrition occur rather than a redesign of the entire course.

METHOD

We studied the dropout rates within single-enrollment university-level online education courses using grounded theory methods as a guide for formulating our hypotheses (Glaser & Strauss, 2009). Our hypothesis before gathering data was that there existed a particular point in a course where a relatively large number of students would drop the course, which we termed the course's Tipping Point. Course by course, we defined the Tipping Point as the lesson after which the most dropouts occurred and dropouts after that lesson represents over 50% of total dropouts. In other words, we looked for the lesson in a course after which at least half the dropouts occurred. Stated differently, if a course had a lesson after which 50% of the total dropouts left the course, we considered that lesson the course's Tipping Point. We hypothesized that the Tipping Point in the course could be redesigned such that fewer students would drop out.

We organized the data first by course and then by the last lesson completed for students who withdrew or had their course expire before completion. Table 1 illustrates how we arranged the data for analysis. An example course XYZ 100 shows that five students dropped out after completing Lesson 1, ten more students dropped out after completing lesson 2, and two more students dropped out after lesson 3 (see Table 2).

We systematically obtained and organized two years of course dropout data for 196 individual university-level online education courses as a means to identify Tipping Points in each course.

Table 1: Descriptive Statistics of Data Set

	n	Mean	Standard Deviation	Range (min/max)
Enrollments	54,393	277.5	326.6	1/3,056
Dropouts	3,144	16.0	30.5	1/205

Table 2 - Dropout Data Organization

Course	Lesson 1	Lesson 2	Lesson 3	...	Lesson N	Total Dropouts	Total Enrolled
XYZ 100	5	10	2	...	0	25	100

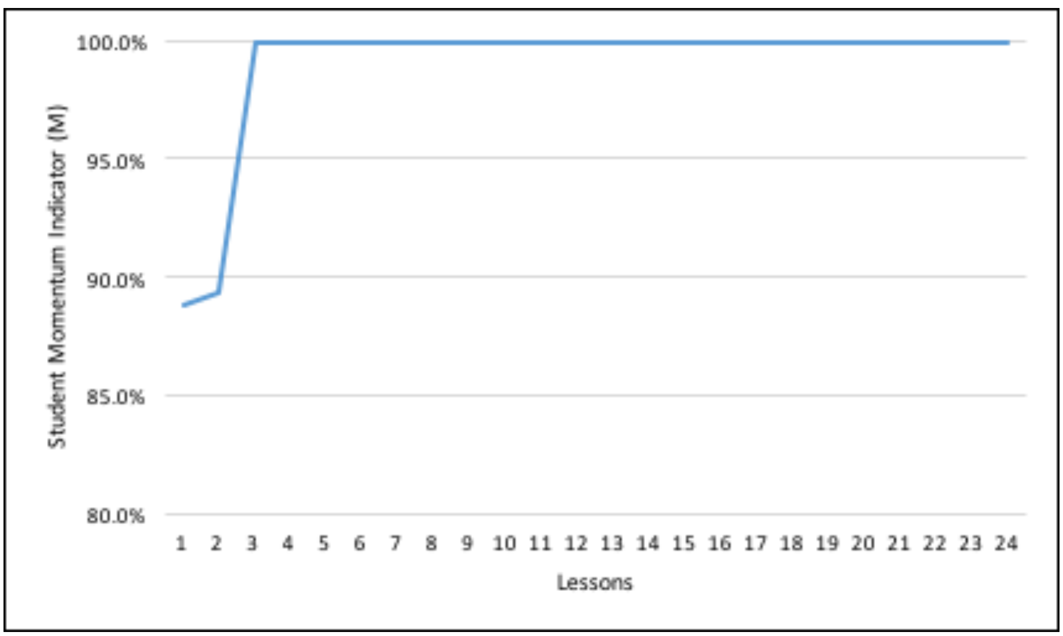
As a result, we found 50 courses, or 25.5% of courses, had Tipping Points, indicating that our initial Tipping Point hypothesis failed to adequately explain the data. In an attempt to better develop a tool for instructional designers, we generated a new theory linking course design to dropout rates using ground theory methods of constant comparing the dropout data across the courses.

With the same arrangement of data and incorporating the total enrolled data point, we put forward a grounded theory called the Student Momentum Indicator ("M"). M equals the percent of students enrolled in the course who finished and M is calculated after each lesson. M = (total enrolled – dropouts remaining after the lesson) / total enrolled

Using the Table 2 data as an example, total enrolled = 100 and dropouts remaining after Lesson 1 = (25 – 5) = 20. Thus, M = (100 – 20) / 100 = 80%. In other words, after Lesson 1, 80% of the remaining students would eventually finish the course. After Lesson 2, where dropouts remaining = (25 – 5 – 10) = 10, M = (100 – 10) / 100 = 90%. Likewise, after Lesson 3, where dropouts remaining = (25 – 5 – 10 – 2) = 8; M = (100 – 8) / 100 = 92%. Eventually, there is a point in the course where there are no more dropouts remaining in the enrolled student population and M = 100%.

It may be easier to understand M when it is graphed across the lessons. When graphed, M visually indicates what we have termed Course Walls (see Figure 1). Course Walls are areas of the course's lesson sequence wherein the student's momentum to finish the course is significantly slowed or halted. In other words, Course Walls come about when groups of students drop out or quit near the same point in the course. Our grounded theory is that by identifying Course Walls, instructional designers can focus their efforts on investigating why students are losing momentum at particular points in the course and revise the course with dropouts in mind.

Figure 1: Graph depicting a Course Wall.



By graphing M for all 196 courses, we employed the constant comparative qualitative method of data analysis (Glaser & Strauss, 1967). Within this method, each graph was considered a case and compared with all other cases—that is, all other course graphs. Inductively, each case was oriented with other cases of similarly shaped graphs to begin to form potentially meaningful categories. We named each category to reflect a description of the dropout behavior and graph shape. After allowing for some abstraction in each category, the number of categories we found maximized each category's illuminating qualities for our intended audience: instructional designers (Guba & Lincoln, 1981). Ultimately, we linked the categories to a tool that better explained the nuances of the dropout behavior than the Tipping Point did. It turns out that the dropout behavior in most courses reflects more complexity than a single Tipping Point.

STUDENT MOMENTUM INDICATOR GRAPH SHAPE CATEGORIES

We found nine categories of M graph shapes using the constant comparative method. Our categorization of graph shapes seen in 196 courses are as follows:

1. Steep wall shape
2. Back-to-back wall shape
3. Steady slope shape
4. Convex slope shape
5. Three wall shape
6. Early and late wall shape
7. Flat slope shape
8. Spanning wall shape
9. Other shapes

Table 3: Frequencies of Student Momentum Graph Shapes

Graph Shape	Frequency	Percentage of Total
Steep wall shape	50	25.5%
Back-to-back wall shape	32	16.3%
Steady slope shape	28	14.3%
Convex slope shape	25	12.8%
Three wall shape	24	12.2%
Early and late wall shape	23	11.7%
Other shapes	7	3.6%
Flat slope shape	5	2.6%
Spanning wall shape	2	1.0%
Total	**196**	**100%**

We describe these categories using a sample of actual courses that serve as examples of each of the eight distinct shapes, excluding the shapes categorized as "Other shapes" (Table 4). It will be helpful to visualize these graphs as depicting the course as a mountain being climbed by the students. The steeper sections indicate where student momentum is slowed. Mathematically, a steeper slope means a larger exodus of students between two lessons.

Table 4: Frequencies of Student Momentum Graph Shapes by Subject

Subject	Steep Wall	Back-to-Back	Steady Slope	Convex Slope	Three Wall	Early & Late Walls	Flat Slope	Spanning Wall	Other Shapes
Business	6.7%	6.7%	60.0%	0.0%	6.7%	20.0%	0.0%	0.0%	0.0%
Comms.	25.0%	0.0%	50.0%	0.0%	0.0%	25.0%	0.0%	0.0%	0.0%
English	25.9%	29.6%	11.1%	7.4%	11.1%	11.1%	0.0%	0.0%	3.7%
Health	50.0%	16.7%	0.0%	16.7%	0.0%	0.0%	0.0%	0.0%	16.7%
History	18.8%	18.8%	12.5%	12.5%	25.0%	12.5%	0.0%	0.0%	0.0%
Humanities	27.3%	18.2%	18.2%	18.2%	0.0%	0.0%	18.2%	0.0%	0.0%
Language	50.0%	8.3%	8.3%	0.0%	25.0%	0.0%	8.3%	0.0%	0.0%
Math	0.0%	0.0%	12.5%	75.0%	0.0%	0.0%	0.0%	0.0%	12.5%
Political Science	63.6%	9.1%	9.1%	0.0%	0.0%	0.0%	18.2%	0.0%	0.0%
Religion	18.8%	12.5%	6.3%	0.0%	31.3%	18.8%	0.0%	0.0%	12.5%
Science	6.7%	6.7%	13.3%	33.3%	13.3%	13.3%	0.0%	6.7%	6.7%
Social Science	28.9%	20.0%	6.7%	15.6%	11.1%	15.6%	0.0%	0.0%	2.2%
Other	20.0%	30.0%	10.0%	0.0%	10.0%	20.0%	0.0%	10.0%	0.0%
Total	**25.5%**	**16.3%**	**14.3%**	**12.8%**	**12.2%**	**11.7%**	**2.6%**	**1.0%**	**3.6%**

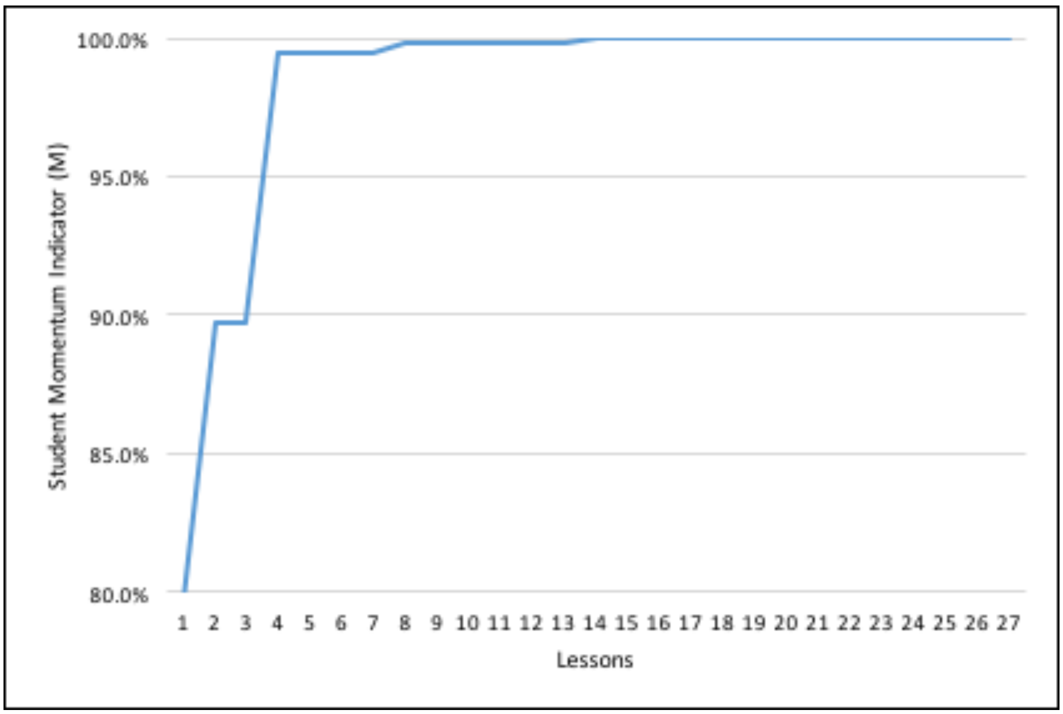
Steep Wall Shape

As Figure 1 illustrates, a relatively steep Course Wall occurred between lessons two and three. This graph shows approximately 89% of students who completed lesson two finished the course; however, 100% of students who completed lesson three finished the course. This indicates that 11% of the students dropped out between lessons two and three. Because this jump between two consecutive lessons is above 5%, we categorized it as a steep Course Wall. Steep Course Walls are where students lose momentum to finish the course. Approximately 25.5% of the courses in this study had a steep Course Wall between subsequent lessons.

Back-to-Back Wall Shape

Figure 2 depicts a course with back-to-back Course Walls, which represented 16.3% of the courses in this study. The back-to-back category is when two Course Walls are within a few lessons of each other. In Figure 2, there is a Course Wall between lessons one and two and then another Course Wall between lessons three and four. When this occurs, the student momentum to finish the course is slowed between lessons one and two and then again between lessons three and four, but not between lessons two and three.

Figure 2. Course graph with back-to-back Course Walls.



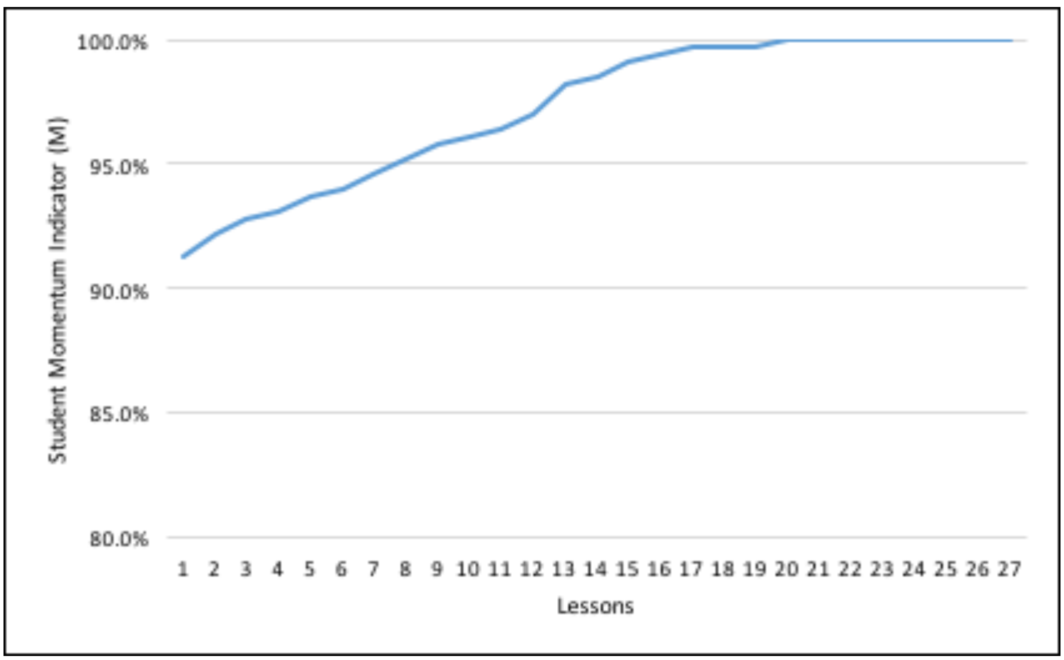
Spanning Wall Shape

When a Course Wall spans multiple subsequent lessons, it is called a spanning Course Wall. In Figure 6, there is a spanning Course Wall between lessons four and six and another spanning Course Wall between lessons 19 and 22. When a Course Wall spans subsequent lessons, it means students continue to drop out after each lesson in the span. In essence, a spanning Course Wall can be thought of as Course Walls stacked on top of each other, similar to a back-to-back shape. Although spanning Course Walls are incorporated into the other shape categories such as steady slope (see Figure 3 for steady slope spanning Course Walls), early and late walls (see Figure 6 for multiple spanning Course Walls), convex slope shape (see Figure 4 for convex spanning Course Walls), back to back walls, and three walls, we found approximately 1.0% of courses as having a single spanning Course Wall.

Steady Slope Shape

Figure 3 depicts a spanning Course Wall between lesson one and twenty; however, because the change in M between subsequent lessons is minimal and the slope is not steep, there doesn't appear to be any remarkable Course Walls. We categorize this shape as a steady slope instead of a spanning Course Wall and this shape was found in 14.3% of the courses studied.

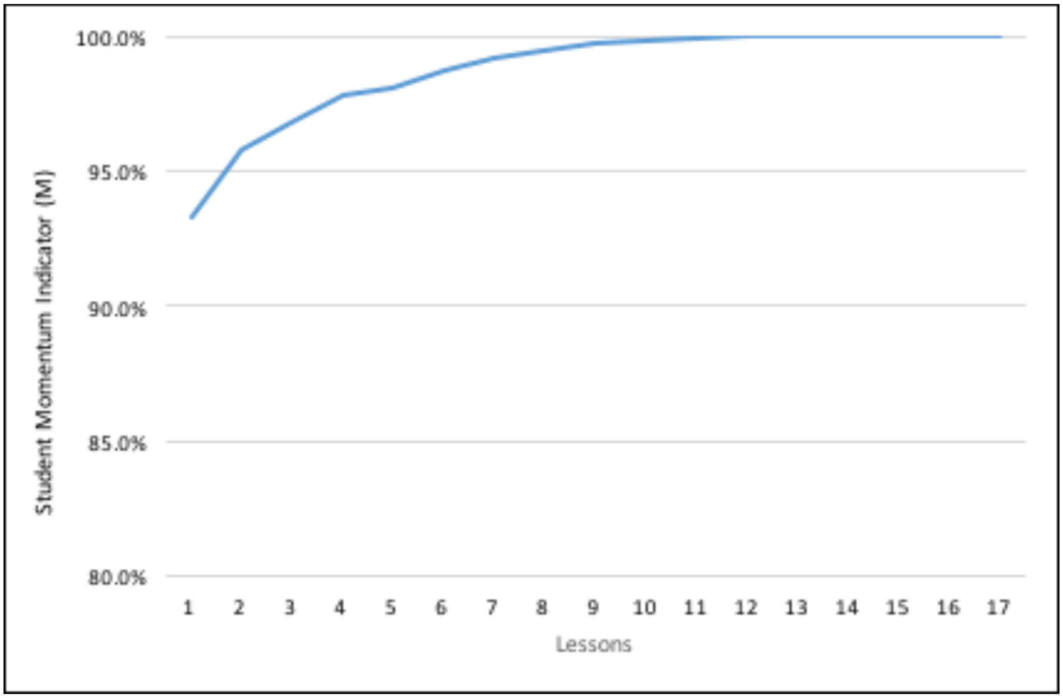
Figure 3: Course graph with a steady slope Course Wall.



Convex Slope Wall Shape

Illustrated in Figure 4, a convex slope is a spanning Course Wall that decreases in its dropout rate with each subsequent lesson. It is similar to the steady slope wall shape except that the majority of dropouts occur earlier in the course instead of a steady rate of dropouts. We found 12.5% of the courses studied had this shaped Student Momentum Indicator graph.

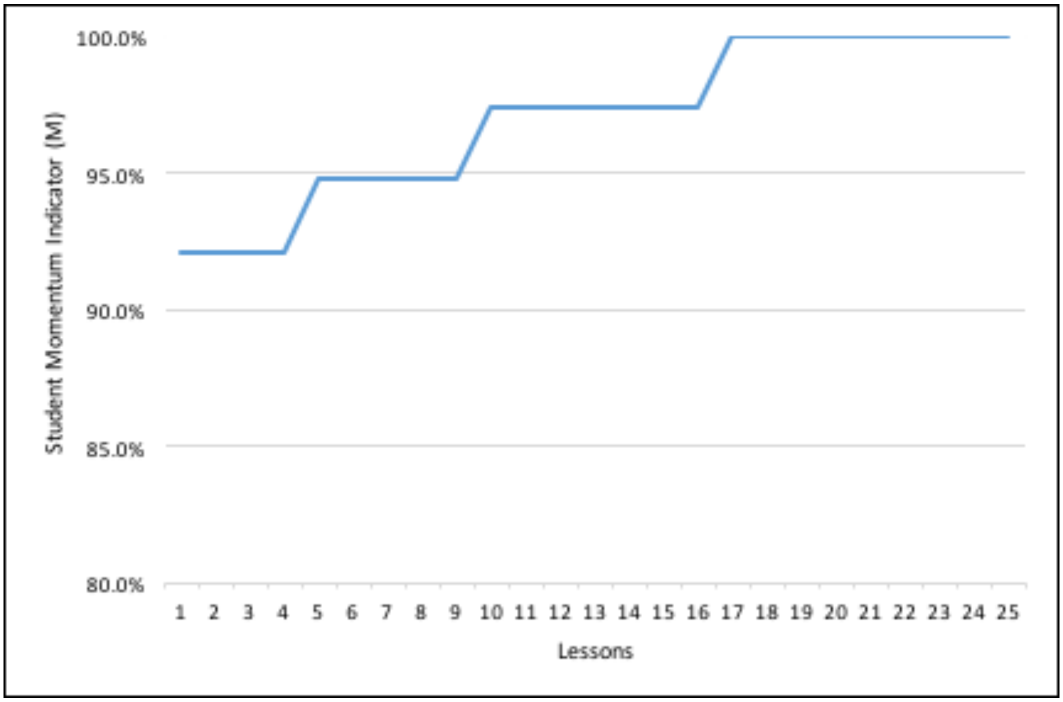
Figure 4: Course graph with a convex slope Course Wall



Three Wall Shape

The Three wall category is when three distinct Course Walls are found within the same course. In Figure 5, there is a distinct Course Wall between lessons four and five, nine and ten, and the third Course Wall occurs between lessons 16 and 17. When this occurs, the student momentum to finish the course is slowed between lessons four and five, again between lessons nine and ten, and yet again between lessons 16 and 17. We found 12.2% of courses in this study to have M calculations of this shape.

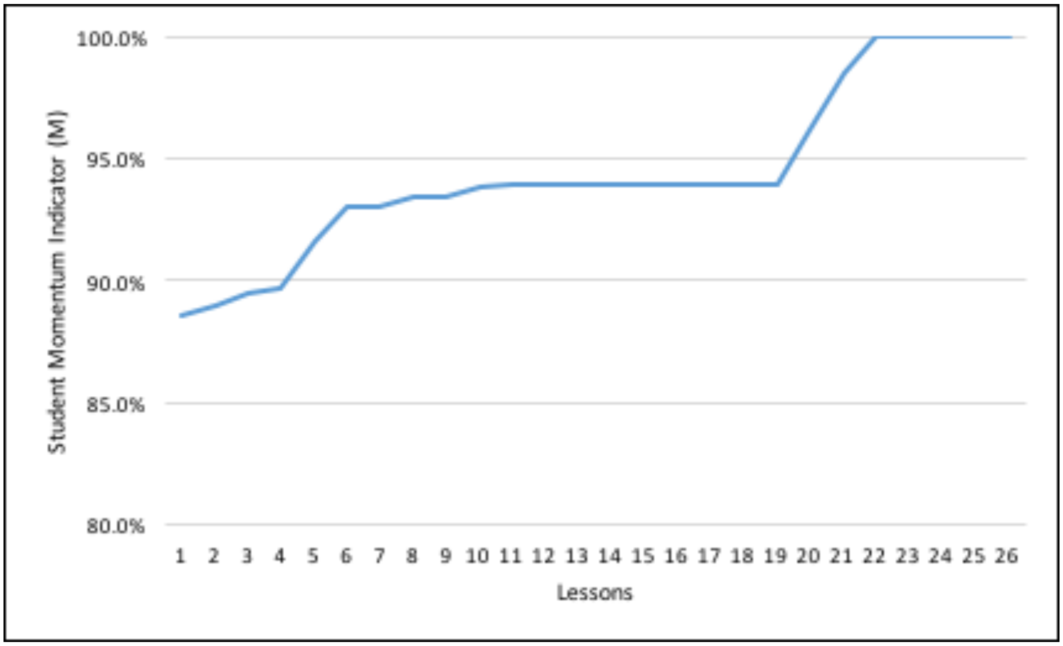
Figure 5: Course graph with three Course Walls



Early and Late Wall Shapes

Figure 1 is a good illustration of an early Course Wall. Because this Course Wall happened within the first half of the course, it is categorized as early. Where early Course Walls happen in the first half of the course, late Course Walls happen in the second half of the course. The late Course Wall in Figure 6 indicates that students are dropping out after having completed about three quarters of the course (see the late Course Wall happening between lessons 19 and 22). An early and late wall shape has a distinct Course Wall in the first half of the course and a distinct Course Wall in the second half of the course. The Student Momentum Indicator calculation (M) showed 11.7% of the courses studied were of this shape.

Figure 6: Course graph with early, late, and spanning Course Walls.

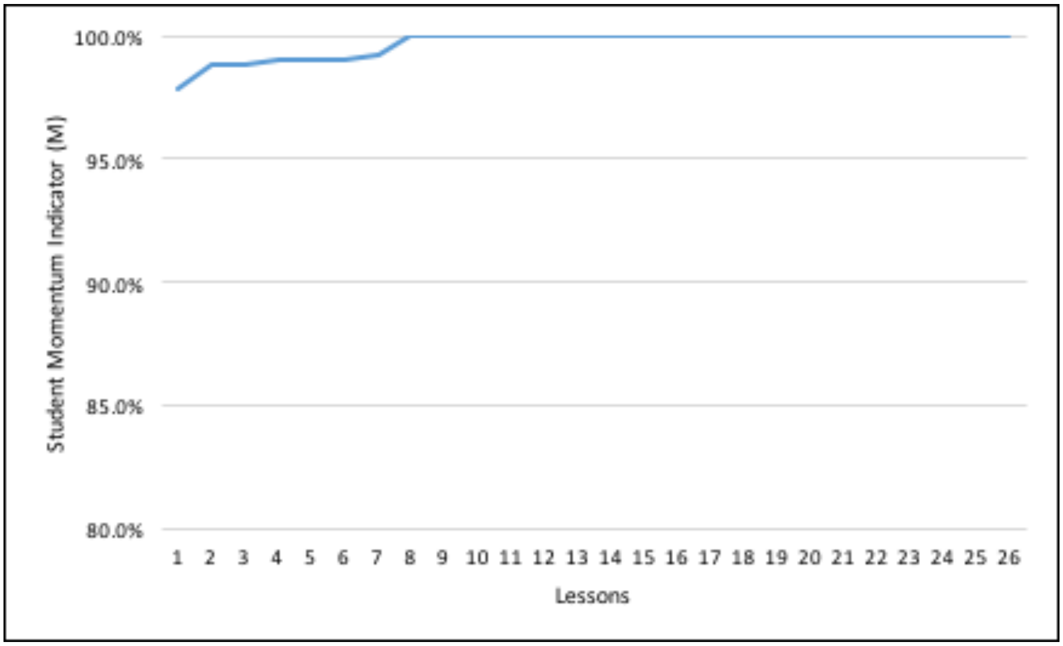


Flat Slope Shape

Shown in Figure 7, this course graph appears flat. After lesson one, very few students drop out and by the middle of the course, no students drop out. This flat shape indicates a course with high student momentum from start to finish. Only 2.6% of courses in this study were categorized as having the flat slope shape.

Distractions in the Students' Environments

Figure 7: Course graph with a flat slope Course Wall.



Other Wall Shapes

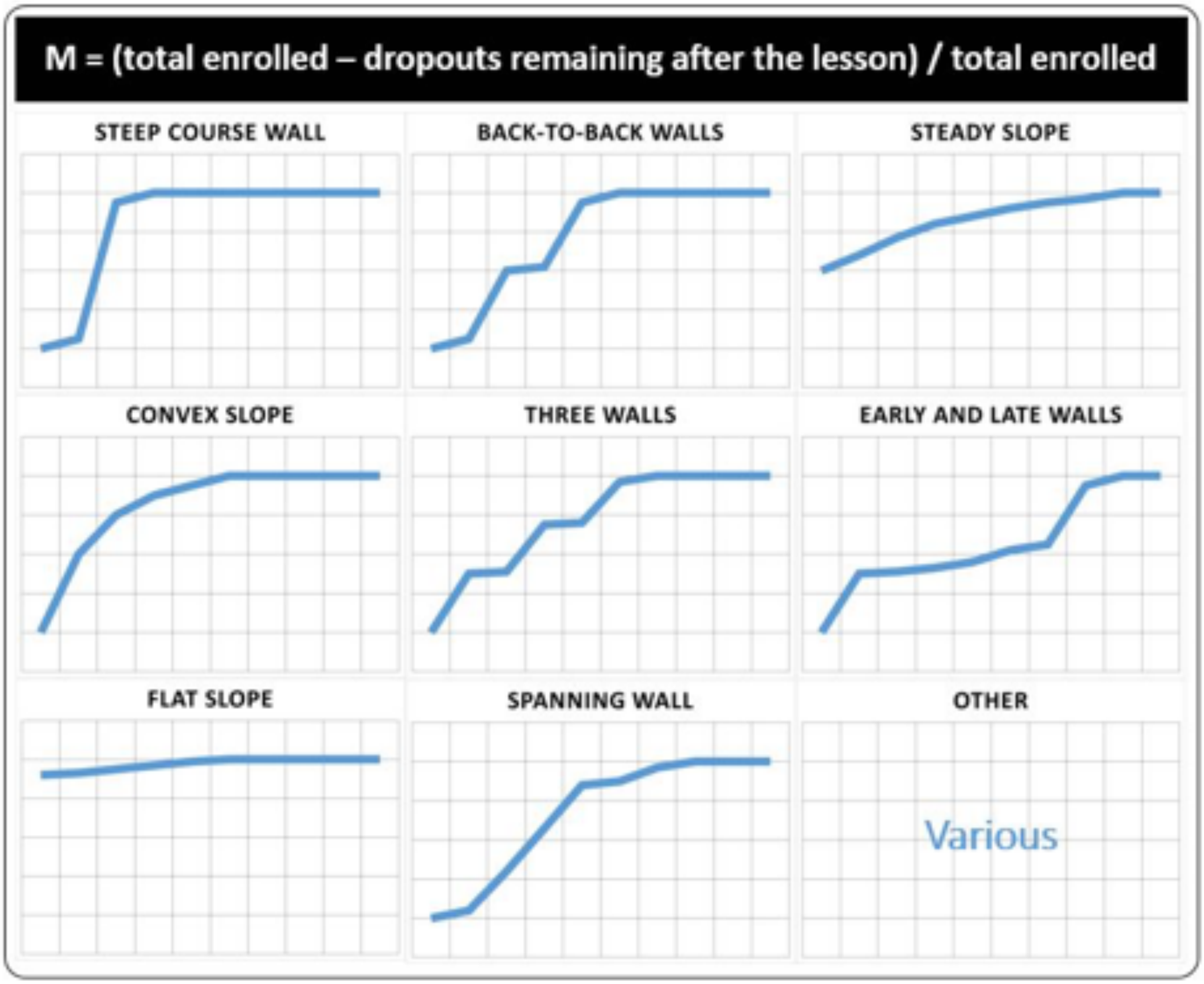
Wall shapes that did not fit the categories described above were grouped into the "other" category. There were very few courses, 3.6%, that could not reasonably be grouped into one of the other eight Course Wall shape categories and didn't represent a new category when combined.

DISCUSSION

The following is a discussion of our interpretation of the M graph shapes. A Course Wall is not necessarily indicative of a poorly designed course, especially if the wall occurs in the first few lessons of a course. It is common for students who do drop out to enroll in an online education course, complete a few assignments, and withdraw. Similarly, in the face-to-face university environment many students adjust their course load well after the first day of the semester. In many of these instances, there are circumstances unrelated to course design that prompt a student to drop a course. Some students drop in favor of a new work schedule while others drop a course only to enroll in a different course. Whatever the circumstance, no amount of course design can account for students making changes to their schedules, which means a Course Wall near the beginning of a course cannot be completely mitigated.

Figure 8 provides a collection of all the graph shapes noted during the analysis of the data. This summary is intended to provide the reader with a visual reference of each graph shape.

Figure 8: All graph shapes noted during research.



Steep Wall Shape

A steep Course Wall indicates a high dropout section of the course where student momentum to finish the course slows considerably. Steep Course Walls are likely caused by a single lesson that appears too difficult, even impossible, where students would rather drop out than complete it. That may be the case in Figure 1 where Lesson 3 is causing a steep Course Wall. Steep Course Walls should be concerning for course providers and designers. Steep Course Walls are excellent targets for quick gains through redesign. The lesson after a steep Course Wall should be evaluated from the perspective that it may be causing students to drop out and how it might be redesign with that in mind.

Back-to-Back Walls Shape

The problem with back-to-back Course Walls is student momentum recovery. Those students who advance past the first Course Wall will eventually regain momentum to finish the course unless they hit another Course Wall without much recovery time. As such, theoretically, if back-to-back Course Walls occur, a student approaches the second Course Wall with diminished momentum from the first Course Wall. Without recovery, overcoming the second Course Wall is less likely. Course designers should pay close attention to back-to-back Course Walls because of their multiplying effect of dropout rates. Both Course Walls need attention, but the latter Course Wall should be the priority for redesign since it is later in the course and students will encounter it with less momentum than the first Course Wall (see late wall shape below). Steady slope shape

Where there is a steady, but not steep, rate of dropouts over most of the course and no well-defined Course Walls, it is difficult to pinpoint problem areas. For example, a steady rate of dropouts within the first quarter of the course may not indicate a need for redesign; however, dropouts beyond the first quarter highlight potential student momentum issues similar to the issues of a late Course Wall or back-to-back Course Walls. Unfortunately for course designers, the lack of a Course Wall shows that there were no large groups of students losing momentum at the same part of the course. Thus, redesign efforts may need to be broader (e.g., overall course difficulty, relevance, instruction quality, etc.) than a focus on specific lessons

Convex Slope Shape

The convex slope of a Course Wall is preferred over the steady slope wall shape because it indicates that more students are dropping out at the beginning of the course creating the convex slope. In other words, the student who eventually drops out is doing so earlier in the course rather than after a significant amount of time and effort has been put into the course. The relative steepness of the beginning of the slope should be targeted by instructional designers because this is an area in the course that could be redesigned and targets more of the dropouts than the lessons further into the course.

Three Walls Shape

The three walls shape indicates three areas of the course where students are dropping out. Similar to the back-to-back walls shape, the three Course Walls are detrimental to student recovery for the same reasons illustrated in back-to-back Course Walls and steady slope shapes. All three Course Walls should be reviewed by course designers, but emphasis should start with the third Wall because of its occurrence late in the course.

Early and Late Wall Shape

Late Course Walls are problematic and perhaps the most detrimental to a student. A significant Course Wall in the second half of the course means there were many students giving up after doing a substantial amount of course work. Course providers have a vested interest in the success of their students and do not expect students to drop out late in the course. Students do not expect to encounter major difficulties late in the course as well. Late Course Walls are perhaps the worst situation for course providers, course designers, and students. As such, lessons where late Course Walls occur should be investigated and redesigned.

Flat Slope Shape

A flat-shaped graph is, in most cases, the desired shape for instructional designers and students. This shape indicates that almost all of students who enroll in the course will complete the course successfully. It is important to note, however, that a flat shape could be an indicator of a course that is too easy. An analysis of grades and other indicators of learning can mitigate the risk that a course is too easy, especially if accreditation issues arise.

Spanning Wall Shape

A spanning Course Wall has a greater multiplying effect on dropout rates than even back-to-back Course Walls. There is some student momentum recovery between back-to-back Course Walls since there are lessons in between with relatively flat M slopes, but there is less of an opportunity for recovery during a spanning Course Wall as students endure several difficult lessons without a break. In other words, a spanning Course Wall drives students to drop out because each subsequent lesson reduces momentum to finishing the course. Course designers should focus on the group of lessons where a spanning Course Wall occurs giving initial priority to the last few lessons.

LIMITATIONS OF THIS STUDY

We studied the phenomenon of students dropping out of an individual course by categorizing the graph shapes of each course's Student Momentum Indicator (M) calculations. We did not study the dropout behavior of students quitting a diploma/degree program or track. We believe the decision to drop out of a whole program is different than that of dropping out of an individual course. Thus, our results should not be applied to program dropouts.

It is also important to note that the Student Momentum Indicator could be influenced by certain student characteristics such as class standing, age, grade-point average (GPA), and propensity to drop out of courses. Individual instructors can also influence the calculation depending on their quality and timeliness of feedback, overall instructor presence, likability, etc.

IMPLICATIONS FOR PRACTICE

As noted above, instructional designers

need tools to assist with specifically decreasing dropout rates. By identifying Course Walls through the graphing of M, our grounded theory helps instructional designers who want to know why students are losing momentum at particular points in the course. The identification of Course Walls on a lesson-by-lesson basis is intended to assist instructional designers in improving online education courses.

Once problematic lessons are identified using the momentum indicator, potential problems that the designer should consider are the quantity and quality of feedback given to the student by the teacher. In addition to instructor feedback, a multitude of other factors could cause Course Walls: the quality of student-student interaction, technological challenges, etc. Once a Course Wall is identified, it is up to the designer to determine the cause of the wall and the appropriate action for course improvement.

To adapt the Student Momentum Indicator to a traditional semester the instructional designer could conduct an analysis of student dropouts using weeks of the semester as opposed to lessons completed. Although, it would be expected to see a spike in withdrawal activity during the week of the institution's add/drop deadline, any spikes in withdrawals after the deadline could indicate a possible issue with one or more lessons taught during that particular week.

As Lee and Choi (2011) noted, course design—that is, interactivity, overall quality, and relevance to student needs—plays an important role in the decision to drop out. We posit that graphing the Student Momentum Indicator (M) is a useful tool for identifying areas of the course where it may lack interactivity, quality, and relevance. Without this tool, instructional designers may connect the overall dropout rate to the conclusion that the entire course needs attention when revision may only be needed in specific areas as indicated by Course Walls.

Additionally, we recognize that most instructional designers are constrained by time and other resources when considering improvements to courses. We also advance this tool as helpful in prioritizing course revisions and areas of the course to be revised. Priorities can be established using the identification of Course Walls through graphing the Student Momentum Indicator (M). When a course is identified with a high dropout rate, before resources are allocated to revise the entire course, instructional designers should identify Course Walls as a method for reducing the expense and scope of the revision. By identifying Course Walls and targeting specific areas of the courses for revision, more courses can be revised within the constraints of time and resources faced by every instructional designer.

Further, a course should not be redesigned for the sole purpose of reducing Course Walls. Designing a course to be particularly easy for students would likely eliminate Course Walls; however, every effort should be made to maintain the pedagogical and academic integrity of the course. The ideal student momentum indicator should be as close to 100% as possible as long as students are able to demonstrate that they are achieving the course learning objectives. This is ideal because it limits dropouts to the beginning of the course.

Identifying Course Walls in nearly 200 courses with over 50,000 enrollments necessarily required "big data" software in our case; however, the Student Momentum Indicator (M) graphs do not. The simple organization of data shown in Table 2 is everything an instructional designer needs to calculate M and a spreadsheet tool could easily handle the graphing. As an instructional design tool, the ease of calculation and graphing make it very accessible for all different sized programs and resources.

The Student Momentum Indicator (M) opens up a wide range of future research options. As an instructional design tool, the following questions are still left unanswered:

- How do instructional designers use the Student Momentum Indicator (M) in their design work?
- Do Course Walls move over time, after a redesign, or based on different student cohorts?
- What impact on design resources does targeting Course Walls have on the design budget?
- Can the Student Momentum Indicator inform design decisions at the subject level (see Table 4) From a student perspective, there are other research questions like:

- How do students react and feel when they encounter a Course Wall?
- What are the main reasons Course Walls exist?
- What resources help students overcome Course Walls?

CONCLUSION

Given the millions of students enrolled in online education courses and their higher dropout rates than face-to-face courses, the need for instructional design tools related to decreasing dropouts is paramount. Disconcerting for instructional designers faced with this issue is the general lack of published design tools of this sort. We conclude that the Student Momentum Indicator (M) and the graphing and categorizing of Course Wall shapes contribute significantly to the instructional designer's ability to address dropout rates in their online education courses. Ultimately, these tools provide a greater insight for redesign resources by prioritizing and targeting course revisions and enabling instructional designers to investigate why students are losing momentum at particular points in the course.

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