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IMPACT OF DATE OF STUDENT ENTRY ON ONLINE HIGHER EDUCATION

Mary Beth McCabe, Point Loma Nazarene University

ABSTRACT

Online education has never been more relevant than after the pandemic in 2020. Many classrooms moved to the online format for the first time. This study looked at how date of student entry and activities in online learning affect final grades and student-reported learning in higher education. The author considered undergraduate and graduate students at an online university to learn whether early entry into a class could predict final grades of students. There was significant correlation between date of student entry and grade, especially for the undergraduate students, with weaker predictability for graduate students. The number of keyboard/course clicks within the online class by a student was found to be a predictor for students' performing well and for those students who were struggling with the content.

JEL: O31, T21, C80

KEYWORDS: Online Learning, Education, Date of Entry, Course Clicks, Perception of Learning

INTRODUCTION

In the post-pandemic era, distance education is required at many colleges. Online learning presents a new era not only for many students, administrators, and faculty, but for education strategists, data analysts, and statisticians. The time has arrived for further understanding of how to support online student learning. Unlike historical planning, which led to stagnation, strategy is used for reorienting learning organizations into new directions for managers and educators (Ansoff, Kipley, Lewis, Helm-Stevens, Ansoff, 2019).

Research shows steadily increasing motivation relating to career and employment goals among online students. Sixty-nine percent of online students identified employment as their primary goal for entering a degree program (Best Colleges, 2019). It is more likely that successful employment could occur if the individual has been successful in college. With thousands or tens of thousands of dollars invested in college tuition and preparation time, graduates may become financially overwhelmed, adding pressure in an uncertain job market (Selingo, 2016).

According to Shacklock (2016), learning analytics includes measurement, collection, analysis, and reporting of data about students and their contexts, to understand and optimize learning and its environments. In a similar definition, predictive learning analytics is looking at statistical measures of historical and current research from learners and the process of learning to create predictive models that improve the learning environment.

Colleges collect data on students, the classes they take, and the grades they receive; however, they are not doing enough to capture the predictions of students' success in data-driven businesses, such as health care, information technology, or even transportation (Anderson & Staub, 2015; Testa, 2008). Higher education needs to look for patterns in attrition rates, based upon student participation and completion of degrees. They need to pay attention to the growing role of educational online environments to find out more about student participation and perception of learning. Tracking time-based data points in the online classroom can bring new insights into education outcomes (Armstrong, 2019). Currently, most data consist of attendance records, graduation rates, and standardized testing. There is a need for more specific, tangible indicators of student outcomes.

The following research questions will be discussed: 1) To what extent does the date of student entry to a class predict the final grade? 2) To what extent does the number of keyboard/course clicks in the online class predict final grade? 3) To what extent does the number of keyboard/course clicks predict student perception of learning? Date of student entry is explored as an indicator of early engagement and adds to the body of knowledge for online education tracking. This study will fill the research gap to better understand if those students who arrive in the online class early earn higher achievement levels. Thus, this study will consider whether date of student entry in the class impacts online learning. The overarching goal of improving educational tracking guidance is for students to become better prepared for the future workforce.

LITERATURE REVIEW

There are promises and pitfalls in online education. It breaks the boundaries of time, space, age, and reality, and it is extremely open (Zheng, Jiang, Yue, Pu, & Li, 2019). Because there is not as much supervision as in a traditional classroom, students must be self-motivated and organized. Online education is free of barriers between students and other students, the teachers, the platforms, or other roadblocks that could get in the way of interaction with learning. Of course, these are also the ways that learning happens in online education. This freedom to learn challenges students' abilities to work independently. There is a positive relationship between innovativeness and using online technologies, especially for those who are seeking information, such as learners (Roehrich, 2004).

Problems with online learning include lack of standards in quality, failing to achieve real learning outcomes, recognizing real learning, and lack of emotions from students online. Using data available from online tools, there has emerged new learning behavior analysis and new techniques for researching these behaviors (Carlson-Landy, 2012). The data of learning behavior is the data generated, such as the number of keyboard/mouse clicks, length of study, progress of learning, and activity, completed by the learner during the learning process (Zheng, et al., 2019). In some instances, students perform worse in the online class, especially if they have a weak grade point average (GPA) at the start of the term (Bettinger, Fox, Loeb, & Taylor, 2017; Bettinger & Loeb, 2017). Online or face-to-face delivery method showed no difference in student learning with undergraduate business students (DiRienzo, Lilly, 2014).

Clicks can be collected in keyboard/mouse clicks to gain insights into how students learn in the online classroom. This tool can be supportive and non-invasive monitoring for faculty to learn students' level of success (Rodrigues, Gonçalves, Carneiro, Novais, Fdez-Riverola, 2013). Some studies found that online and offline learning are essentially similar. Interactive learning in the online classroom can be essentially the same as learning in on-campus classes regarding pass rates, final exam scores, and performance on standardized tests (Bowen, Chingos, Lack, & Nygren, 2014).

Research in the online classroom considers relevant factors such as knowledge level, student demographics, and final grades with Pearson correlation coefficient algorithms. Zheng's research team in China used this Pearson correlation coefficient methodology and found that, although there were several problems with online learning, there was a correlation with the number of logins, time spent learning, and interacting led to increased student scores in the class (Zheng, et al., 2019). Time spent learning may be connected to personalities or lifestyles (Settle, Alreck, & Glasheen, 1978; Valette-Florence and Usunier, 2001). Personal value systems can contribute to how people spend their time which, for students, can amount to many hours spent in formal learning.

Education researchers (Zheng, et al., 2019) looked at online students in China to find out their learning behaviors. The researchers developed a neural network classification algorithm to see what factors affected student performance, using big data or machine learning to predict future outcomes. Overall, the researchers hoped to improve learning efficiency by studying which practices work for transforming education to the online classroom. Predictors of success include age and experience in online classes (Carson, 2011).

Predicting how students will achieve and complete at scale with big data has been studied to better understand students at risk of not completing their degrees (Herodotou, Rienties, Verdin, and Boroowa, 2019). Predictive Learning Analytics (PLA) says that it is necessary to capture and analyze the perceptions of those educational stakeholders, such as managers, teachers, and students. Teachers would like to predict which students might be at risk of failing in their class (Ferguson, 2012). Procrastination can affect final grade performance for online students in higher education, measured from the date of first access to the date of the first test (Elvers, Polzella, & Graetz, 2003).

Scaling predictability of student success or failure is a longitudinal challenge for the future (Herodotou, Rienties, Hlosta, Boroowa, Mangafa, & Zdrahal, 2020). Companies like Teradata are looking at this in new ways today. Tracking time that students spend in the online classroom produces new insights from the data and may predict what the grade will be based on factors, such as start times and end times in the platform. They can also track when students take a break, move to another learning resource, and track geography of students while learning on the go (Armstrong, 2019). Digital devices most people carry may also unlock new skills for advanced learning. Mobile devices from companies such as CourseKey now collect classroom data for attendance and participation.

In a study that analyze student engagement, student log times, tone and narrative, and keyboard/mouse clicks were collected in the form of days active, weeks active, forum posts, videos watched, problem submissions, time on task, and average problem score (Fincham, Whitelock-Wainwright, Kovanovic, Joksimovic, van Staalduinen, & Gasevic, 2019). The data revealed that academic and behavioral engagement are complicated. The conclusions were that each student's background and the course design must be considered for determining levels of engagement.

The response rates for end of course surveys can be problematic for measuring the adequate validity and reliability (Nulty, 2008). The challenge is to get a high response rate from students to self-report what they learn, especially if students never see the results of their responses. Infrequent, short, simple, and anonymous results should be displayed after the student completes a surveys (Moss & Hendry, 2002). Electronic End-of-Course surveys are best practices for educators when they require this consistently (Eveslage, Wilson & Dye, 2007). Online education student surveys were conducted (Eom & Ashill, 2016), and the strongest predictors of user learning outcomes were course design, instructor, and dialogue. Eom & Ashill, 2016 found that intrinsic student motivation affected learning outcomes.

DATA AND METHODOLOGY

The following research questions will be discussed:

To what extent is the date of student entry to a class predict the final grade?
To what extent will the number of keyboard/course clicks in the online class predict final grade?
To what extent will the number of keyboard/course clicks predict student perception of learning?

The data set contains a total of 516 cases with 296 cases undergraduate students and 220 graduate students. Multiple sections of one undergraduate and one graduate level course at National University were reviewed during an 18-month period for analysis of date of student entry as a predictor of academic success for these students. In addition to final grade data, self-reported data was collected through End of Course (EOC) surveys. Data sets were analyzed to look for predictors. Multiple Regression Analysis will determine the predictors of student success. The primary dependent variable Y is student final scores in the course (0 to 100). The independent variable X is the date that the student enters the class for online learning, (day 1, 2, 3, etc.), as time stamped by the course electronic signature. Students can enter the class on day 1, one day before the official start date, at the earliest. Each keyboard/mouse click represents one student making one entry one time in the online class and are presented as totals for the term. That independent variable was collected to see the relationship to final grade. No other personal or demographic data is used for this study, which is discussed in the limitations. Correlation will describe the degree of association or concomitant variation between the two independently measured traits.

Student course data comes from National University's Learning Management System (Blackboard) via the University's Center for Institutional Learning (CIL), and EOC data is from the Institutional Research Department. Student enrollment and grade information were matched with hidden identification numbers. Dates of entry and perception of learning were tied to a specific student ID. The student ID info is hidden and anonymous. Students take one course per term, which lasts four weeks. Student data is voluntarily collected monthly through the EOC surveys from several different full time and part time faculty members teaching these classes during the study duration, which was 18 months and 18 courses, half graduate and half undergraduate. Students indicate their own Perception of Learning, i.e., "gain significant knowledge about this subject" (ranked 0-5, 5 is highest), which was a second independent variable. This data was all previously collected. No human subjects were identified, and IRB permission was granted in advance of the study.

Information on withdrawn students was removed from the data findings because of no final grade in the class. Dropping classes and attrition could be related to specific instructors or personal life issues, not just with the content and ability to learn, and is a threat to internal validity. There were often 4 to 5 students per class who dropped within the first ten days of the class.

A set of linear regressions and quadratic regressions were performed on the student data. The independent variables include First Access Day (date they log in to course) and Course clicks (keyboard/mouse strokes), both of which are numeric variables. The dependent variable for the main model is the total grade across undergraduate and graduate students. One additional dependent variable is Perception of Learning. Perception of Learning was measured for one third of students (n = 172) in the data sets. Total grade was measured for all students.

RESULTS AND DISCUSSION

The following are the findings of the analyzed data from the predictors of student success study. The analysis indicates relationships in both engagement and activity as they relate to the final grades and reported learning in higher education for online classes.

Research Question 1. To what extent did the date of student entry to a class predict the final grade? Date of student entry was more correlated with undergraduates, therefor a steeper regression graph. (.14) than with graduates (.06). The formula for this relationship is slightly different due to different course point values for total grades.

$$Total\ Grade\ =\ -0.369 * First\ Access\ Day\ +\ C\ (constant)\ for\ undergraduates \tag{1}$$

$$Total\ Grade\ =\ -0.236 * First\ Access\ Day\ +\ C\ (constant)\ for\ graduates \tag{2}$$

Undergraduates may have been less engaged with the learning platform and with online education resources in general, so date of entry was a significant factor. The first day they access could help determine what their grade is, all other factors being equal. Those who start early may be more eager to learn, prepared, engaged, and earn higher grades (Table 1).

Research Question 2. To what extent did the number of keyboard clicks in the online class predict total final grade? Keyboard clicks impacted the student grades only to a certain level. The study found the more they clicked, the higher the grade; after a point, these clicks indicated the desperation of a student struggling with the content (Figure 2). The formula for this relationship for undergraduates is:

$$Total\ Grade\ = -0.0000392 * CourseClicks\ SQ(Squared\ Term)\ +\ 0.185 * CourseClicks\ +\ C\ (constant) \tag{3}$$

Research Question 3. To what extent did the number of keyboard clicks predict student perception of learning level? The number of keyboard clicks has a correlation (R square=0.152) that can indicate a positive perception of learning to a certain threshold (Table 3).

$$Perception\ of\ Learning\ = -1.1 * CourseClicksSQ\ (Squared\ Term)\ +\ 2.469 * CourseClicks\ +\ C\ (Constant) \tag{4}$$

Figure 1: Total Grade (Undergraduate) to First Access Day Correlation

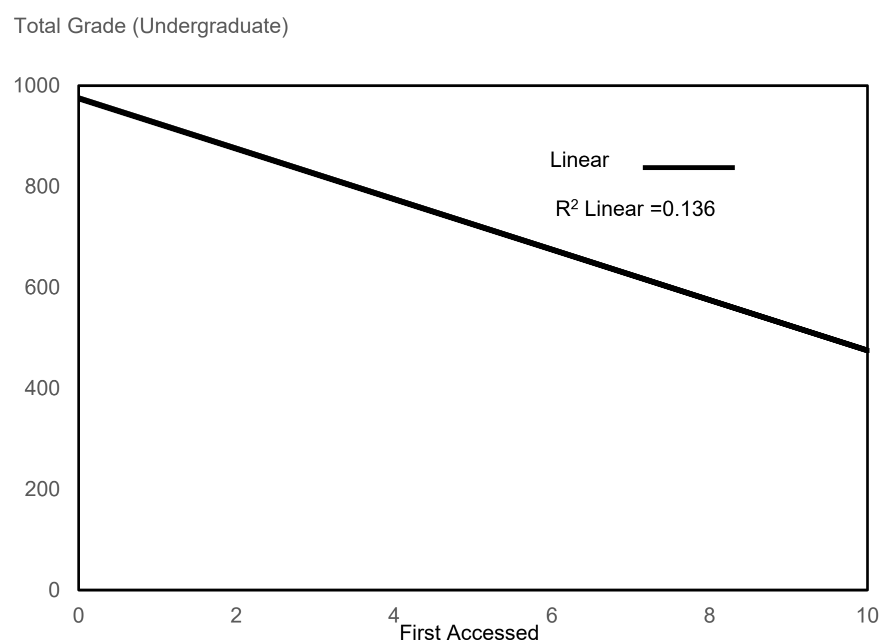


Figure 1 shows a negative correlation (R square= 0.136) This means that students who access the online class in the early days will more likely have higher grades at the end of the course. There is a negative, linear relationship between these two factors total grade and date of student entry to class.

Table 1: Undergraduate, Graduate Students First Access Day to Total Grade, Undergraduate Students Course Clicks to Total Grade

R	R Square	Adjusted R Square	Std. Error of the Estimate
Undergraduate Students First Access Day to Total Grade			
0.369	0.136	0.133	122.4669
Graduate Students First Access Day to Total Grade			
.236	0.055	0.051	169.9516
Undergraduate Students Course clicks to Total Grade			
0.320	0.102	0.096	125.0428

The first two sections of the table show the linear negatively correlated relationship between First Access Day and Total Grade for undergraduate students (0.136) and graduate students (0.055). The third part of the table shows a non-linear pattern, a correlation between undergraduate students Course Clicks to Total Grade (0.102).

Research Question (1) To what extent does the Date of Student Entry to a class predict the total grade?
A linear, negatively correlated relationship between Date of Student Entry and Total Grade (i.e., is found (P <.0001) for undergraduate students. This means the earlier a student accesses the course materials, the higher their total grade will be. The first access day accounts for 14% of the variance in a student's final grade. (R2 = 0.136) Figure 1 and Table 1 shows that there is a significant relationship (14%) between date of entry to a class and the final grade.

As with the observations on undergraduates, a linear, negatively correlated relationship between first access day and total grade (i.e., Total Grade) is found (P <.0001) for Graduate Students. This means the earlier a student accesses the course materials, the higher their total grade will be. However, for graduate students, the effect of the first access day is much smaller with a R2 at 0.055 explaining approximately about 6% of the variance in the student's total grade (Table 1). This leaves a great deal of room to think that there could be other much stronger predictors on the total grade for graduate students. Table 1 indicates that there is not as strong a relationship for accessing the class early, as we saw with undergraduate students.

Research Question (2) To what extent will the number of keyboard clicks in the online class predict the final grade?

The study considered the relationship between undergraduate students' course clicks and total final grade (Table 1). Unlike first access day, course clicks do not translate into a straightforward linear increase on total grade. Course clicks has a non-linear, quadratic relationship with total grade (R2 = 0.102). This means the total grade will tend to go up when the student's course clicks increase.

However, after a certain threshold, increases in course clicks will result in a lower total grade. The implication is when course clicks exceed a certain threshold, that could signal to the teacher that a student might be challenged with the course materials. Based on this data, the finding in Table 4 indicates that there two types of students, one who clicks as they learn and another who click when they are not understanding the course content, which is demonstrated by the slope after the quadratic curve hits the peak in Figure 2. Table 4 indicates both the linear regression term and the quadratic regression term are statistically significant.

Table 4: Undergraduate students Course Clicks Regression Coefficients[a]

	Unstandarized Coefficients		Standardized Coefficients		
	B	Std. Error	Beta	t	Sig.
(Constant)	693.154	30.771		22.526	***
Course clicks	0.185	0.142	0.791	4.461	***
CourseClicksSQ	-0.0000920	0.000	-0.548	-3.090	***

*[a]Dependent Variable: Total Grade. ***, ** and * indicate significance at the 1, 5 and 10 percent levels respectively.*

Figure 2 indicates the quadratic equation for undergraduate students of the total grade to course clicks indicating course clicks' positive relationship with total grade up until the peak in the curve. Note that the bulk of the clicks are between 500 and 1500 clicks.

Figure 2: Undergraduate Students Total Grade to Course Clicks Squared

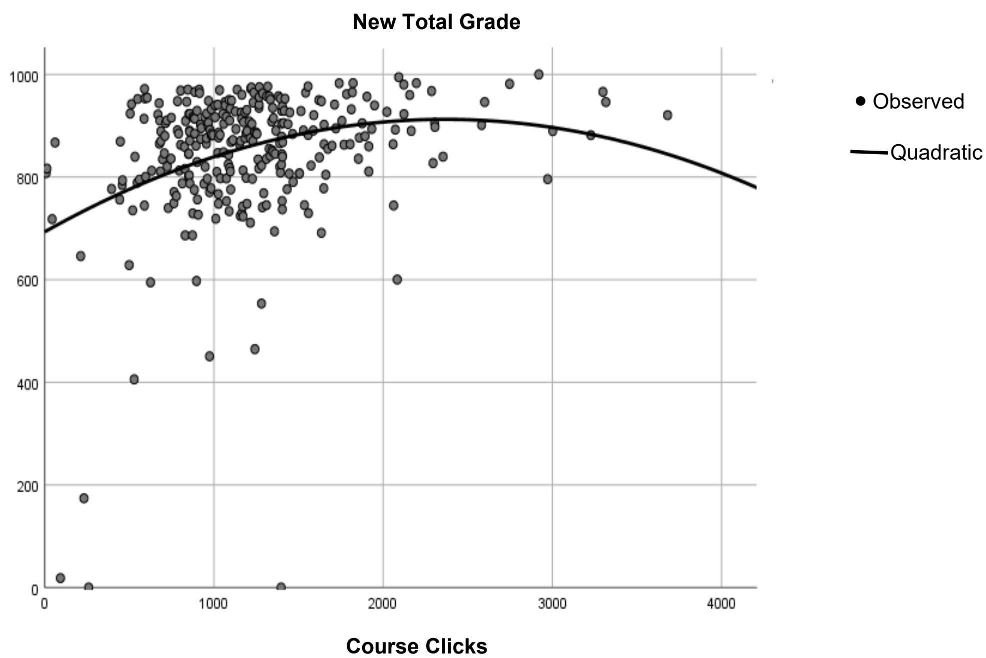


Figure 2 shows the relationship between Undergraduate Students Total Grade and Course Clicks. Each dot represents one student. Most students have between 500-1500 clicks in the course and most grades are between 85-95% in this figure.

In the case for graduate students, course clicks have a small but significant, positive linear relationship with total grade (R2=0.073, *P*<.0001). The formula is Total Grade = 0.271*First Access Day + C(constant). There is no figure presented because the quadratic equation line would not be meaningful.

Table 3 Graduate students Course Click and Total Grade; Course Clicks and Perception of Learning

R	R Square	Adjusted R Square	Std. Error of the Estimate
Graduate Students Course Clicks and Total Grade			
0.271	0.0723	0.069	168.3367
Graduate Students Course Clicks/Perception of Learning Model Summary			
0.390	0.152	0.134	0.843

Table 3 includes the graduate students course clicks in summary. The first section is about the graduate students' course clicks and total grades. Graduate student course clicks have a small but significant, positive linear relationship with total grade (R2=0.0723, P<.0001). The second section is about graduate students clicks and the perception of learning from end of course evaluations. The number of keyboard clicks has a correlation (R square=0.152) that can indicate a positive perception of learning.

Research Question (3): To what extent will the number of keyboard clicks predict student perception of learning?

Course clicks are not found to be significantly correlated with perception of learning among undergraduate students. Unlike the observations on undergraduate students, course clicks are found to have a significant correlation with perception of learning for graduate students (*P*<.001). Specifically, an increase in course clicks translates into a positive perception of learning up until a certain threshold. Table 3 includes the graduate students course clicks in summary. As mentioned earlier, the formula is Perception of Learning = -1.1*CourseClicksSQ (Squared Term) + 2.469*CourseClicks + C(Constant).

Table 4 provides the influence of course clicks on the perception of learning for graduate students in the unstandardized and standardized coefficients. What this shows is that there is an increase in perception of learning as course clicks increase to a certain level or threshold, and then the perception of learning starts to decline despite even more increases in course clicks, which may be evidence of a student's struggle.

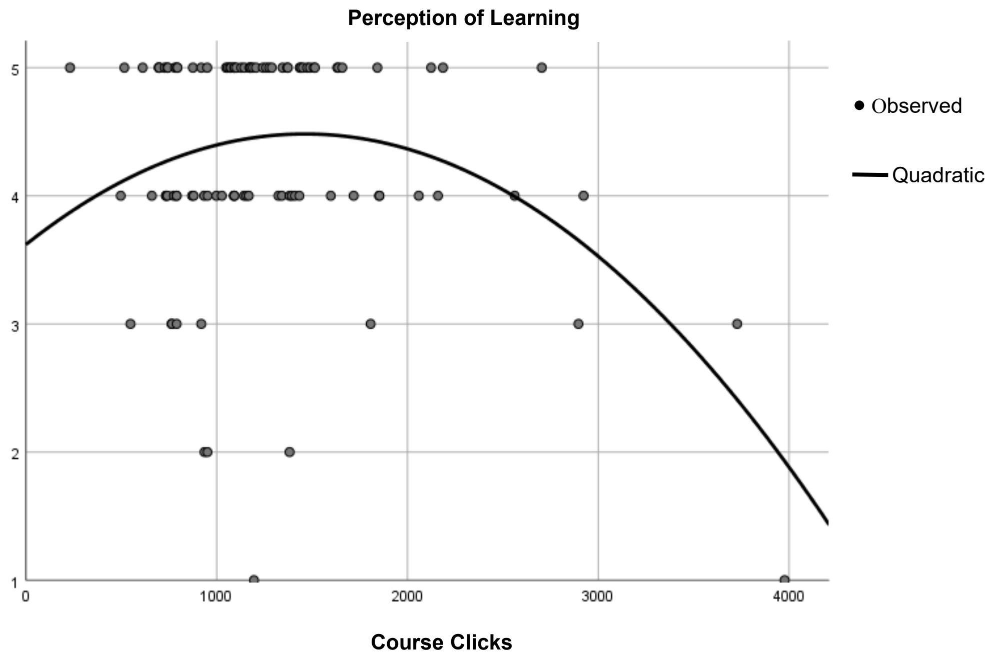
Table 4: Graduate Students Perception of Learning to Course Clicks Coefficients[a]

	Unstandarized Coefficients		Standardized Coefficients		
	B	Std. Error	Beta	t	Sig.
(Constant)	3.620	0.389		9.304	. ***
Course clicks	0.001	.000	0.822	2.469	**
CourseClicksSQ	-0.0000004037	.000	-1.100	-3.303	***

*Dependent Variable: Perception of Learning. Table 4 provides the course clicks on the perception of learning for graduate students in the unstandardized and standardized coefficients. With the increase in perception of learning, as course clicks increase to a certain threshold, the perception of learning declines, which may be evidence of need for help. ***, ** and * indicate significance at the 1, 5 and 10 percent levels respectively.*

Figure 3 indicates the perception of learning for graduate students and the correlation to course clicks (CourseClicksSQ) where there is an increase to a level, but afterwards, there is difficulty and the perception of learning indicates a struggle with the content.

Figure 3: Perception of Learning to Course Clicks



The number of keyboard clicks to graduate student perception of learning has a correlation (R square=0.152) that can indicate a positive relationship up until a certain threshold and afterwards, there could be a struggle of learning reported by students in end of course surveys (Table 4, Figure 3).

CONCLUDING COMMENTS

The study in summary was to better understand what successful student behavior data tell us. If accessing a class early will lead to a higher grade, higher perception of learning and more success, these are outcomes sought in the research. The data method in summary was reviewing 516 university student records of course activities, including date of access, course clicks, perception of learning, and total grades.

The findings in summary indicate that there are two segments of students: 1) students who study hard in the online classroom and do well and 2) students who are failing, but may not be able to get support and, therefore, fail. It would be good for the latter to have extra time for study or tutoring programs, such as 1-on-1 time with an aide or assistant teacher while the students are still in the course, rather than later.

Because date of access is somewhat relevant, but less predictive of student success, it could be recommended that students get a jump on their class early. Faculty can influence this by encouraging messaging and over-communication in the early part of the term or forming buddy groups for learning on day one. However, this may not influence the student's own perception of learning. If teachers are aware that there is a correlation between clicks and grades, and guidance provided about the data, perhaps they could determine what the student learning threshold is and, for students who struggle to that level, there could be an alert set in advance for the instructor to better identify those students who are more likely to fail and help them.

Based on the summary of findings, one of the recommendations may be to allow students to enter the class before the official start date, especially if it is their first online class. Students could become more familiar with the content, the format, the structure, and the outcomes that are expected. Those who start early may be better planners, so students can be encouraged to know that early starts make a difference in final grades for some students, especially the undergraduates, with less education experience.

The limitations are that this study was conducted at only one university and in only one discipline. The variables did not reflect any demographic data or personality indicators. Attrition of students could invalidate some of the findings. For perception of learning, students self-selected. This may not have been representative of less engaged students, and it was completed during the final days of the class. Student learning may not always be recognized while still in the course. In the original study design, the author tried to find student satisfaction through annual graduation surveys, but the response rates were too low to include in this study (10%).

Future research could overlay student records, such as GPA, ethnicity, gender or number of courses completed. Other insights could come from personality characteristics of students to give additional insight to predict student success. Future considerations to minimize any threat to validity could include pre- or post-tests, i.e., students could be asked to participate in a survey. This survey could utilize a mixed methods approach, with both quantitative and qualitative research.

Further research could be about the distribution of the clicks. The more successful students may have an even distribution of clicks over time, while the struggling students may have bursts when they suddenly focus on an element that challenges them. Other research on date of entry could expand the sample size, with different academic disciplines, and long-term studies to correlate graduation rates of those who access early consistently. If students improve with each class, and they take between 10 and 30 courses, this could be extrapolated over their academic career. A study could look at students who arrive on later dates to see if they also turn in assignments late. Since day of access was clearly not the only predictor of final grades for graduate students, it would be interesting to test for other factors to learn more. This study could help create better course survey questions for student end of course assessments and post-graduation, for longitudinal data.

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BIOGRAPHY

The author, Dr Mary Beth McCabe, is a Professor in Marketing at Point Loma Nazarene University. She has taught at seven other universities and owned a marketing consulting firm since 1993. Her research interests include Marketing, Digital and Social Media, Hispanic Marketing.