The Effect of Term Length on Student Achievement in Online College Algebra

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Abstract

Accelerated term lengths are becoming increasingly popular among online colleges. Students can now complete a college course in as little as 4 weeks. Accelerated term lengths can be attractive to students, but it is important to determine the effect of term length on student achievement. This study, grounded in the adult learning theories of andragogy, self-directed learning, and transformational learning, sought to understand the nature of the relation between term length and student achievement in an online college algebra class. A Mann–Whitney *U*-test was performed with a sample of 812 students from the researcher's 8-week and 16-week online college algebra classes. Findings indicated no statistically significant difference in achievement, as measured by the course final exam, between the two groups. This suggests that accelerated term lengths in mathematics are a viable choice for online students.

Keywords: *term length, online learning, mathematics, college algebra*

El efecto de la duración de términos en el éxito estudiantil en clases de álgebra por internet

Resumen

Las duraciones de término aceleradas están siendo cada vez más populares en las universidades en línea. Los estudiantes ahora pueden terminar una clase de universidad en tan solo cuatro semanas. Los términos acelerados pueden ser atractivos para los estudiantes, pero es importante determinar el efecto de la duración de los términos para el éxito estudiantil. Este estudio, basado en las teorías de aprendizaje de adultos (andragogía, aprendizaje autodirigido y aprendizaje transformacional) buscó comprender la naturaleza de la relación entre la duración de los términos y el éxito estudiantil en una clase de álgebra por internet. Una prueba U de Mann-Whitney

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fue llevada a cabo con una muestra de 812 estudiantes de las clases de álgebra en internet de la investigadora en periodos de 8 semanas y 16 semanas. Los hallazgos indicaron que no hay una diferencia estadísticamente significativa de éxito entre los dos grupos, como fue medido a través del examen final de la clase. Esto sugiere que los términos acelerados en matemáticas son una elección válida para los que estudian por internet.

Palabras clave: *duración de términos, aprendizaje por internet, matemáticas, álgebra de universidad*

学期长短对在线大学代数课程学生成绩的影响 美国公立大学系统

摘要

缩短学期在在线高校教育中变得越来越受欢迎。现在学生只需4周就可以完成大学课程。缩短学期对学生很有吸引力，但明确学期长短对学生成绩的影响非常重要。本研究以成人学习理论、自我导向学习理论和转型学习理论为基础，寻求了解在线大学代数课程学期长短与学生成绩关系的本质。该研究对由812个学生组成的样本进行了曼-惠特尼秩和检验(Mann－Whitney *U*-test)。这些学生来自研究人员所在的在线大学，分为两组参与了为期8周和16周的代数课程。结果显示，两组学生期末考试成绩数据并无显著差异。这表明从数学分析，缩短学期对在线学生而言是一个可行选择。
关键词：学期，在线学习，数学，大学代数

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There is a trend among online higher learning institutions toward accelerated courses (Collins, Hay, & Heiner, 2013; Rodrigue, Fanguy, Soule, & Kleen, 2016). With courses commonly offered over 11, 8, or even 4 weeks, earning a degree can now be done in a fraction of the time. While this might have great appeal for students, how does it affect their achievement? More specifically, what is the impact of term length on student achievement in online college-level mathematics?

This study sought to determine if students who complete a 16-week online college algebra course have different levels of achievement than students who complete an equivalent 8-week online college algebra course. Final exam scores from students taking college algebra at a large online university were analyzed to compare achievement levels as they relate to term length. Descriptive statistics were generated, and a Mann–Whitney *U*-test was used to compare the final exam scores for the two groups.

For many undergraduate degree programs, three credit hours in mathematics are required for graduation, yet students often struggle to meet this prerequisite. It is not uncommon for students to wait until the end of their degree program to complete the mathematics requirements. Mathematics can become the gateway to graduation; therefore, is important to determine how best to meet students' needs. If there is a significant difference in achievement levels by term length, then further research can be conducted to identify other factors that impact achievement and proactively help students determine the best path toward success.

Literature Review

It stands to reason that an understanding of mathematics stems from sufficient time to learn the material and opportunities for practice, among other factors (Vilardi & Rice, 2014). In the case of mathematics that is learned online, there is an extra layer of consideration, such as strong time management skills (Bonk, Lee, Kou, Xu, & Sheu, 2015). In addition, Mensch (2013, 2015) notes the important role of student learning style in the online classroom and recommends that developers of online mathematics classes incorporate content that supports multiple learning styles. It should be noted, however, that some researchers disagree with the effectiveness of instruction that is based on learning styles. In a review of multiple such studies, Cuevas (2015) found that learning styles-based instruction is commonly used in practice, but does not offer specific benefits to student learning.

Research in the area of student achievement in the online mathematics class is plentiful, albeit contradictory. In a study of mathematics students, Kavitha and Sundharavadivel (2012) found that the students who were taught via online methods scored higher on an achievement post-test than the students who were taught under a traditional classroom model. Dissimilarly, Vilardi and Rice (2014) determined that online mathematics students had significantly lower achievement scores (as measured by final course grades) than students in a face-to-face setting. Furthermore, students in the face-to-face classroom had a significantly higher proportion of A grades as compared to the significantly higher proportion of F grades in the online classroom (Vilardi & Rice, 2014).

In addition to the course delivery format, other factors affect student achievement in mathematics. Kim, Park, and Cozart (2014) identified student motivation, achievement emotions, and self-efficacy as factors that influence achievement in online mathematics courses. With the goal of determining why some students succeed in online mathematics classes while others do not, the researchers found that achievement emotions (i.e. boredom, anger, and enjoyment) were the most significant predictors of student achievement (Kim et al., 2014). The findings suggest that self-efficacy can be moderated by emotional experiences and that a focus on improving students' motivational experiences could lead to increased achievement (Kim et al., 2014).

In a similar study, Hodges and Kim (2010) used email to deliver self-regulation strategies to students and sought to determine if a relation exists between achievement and the use of self-regulation strategies or self-efficacy. Zimmerman (as cited in Hodges & Kim, 2010) lists the three components of self-regulation as behavioral, environmental, and personal. Studying college students enrolled in an asynchronous, online mathematics class, the researchers grouped the students into three categories where one group received self-regulation strategies with personalized email messages, one group received the same emailed strategies without personalization, and the third group did not receive any strategies (Hodges & Kim, 2010). The personalized email messages embedded self-regulation strategies to help students plan, set goals, and self-monitor their learning (Hodges & Kim, 2010). They found that although the email messages did not lead to a positive change in self-efficacy or self-regulation, there was a positive relation between students' self-efficacy and achievement (Hodges & Kim, 2010). Given that the course was a university requirement and not in the majors of most students, there may have been a lack of self-efficacy among the students which led to a lack of implementation of the self-regulation strategies (Hodges & Kim, 2010).

Term Length

While studies abound on topics such as learning preferences (Bonk et al., 2015), motivation (Kim et al., 2014), persistence (Kranzow, 2013), grit (Duckworth, Peterson, Matthews, & Kelly, 2007; Smilie & Smilie, 2017), and the aforementioned achievement (Hodges & Kim, 2010; Kavitha & Sundharavadivel, 2012; Vilardi & Rice, 2014) in online education, the literature on term length in the online classroom is limited (Rodrigue et al., 2016). Even more limited is the literature on the role of term length in online mathematics classes. Term length has been the subject of research in the face-to-face classroom with findings relevant to the online setting. Both Murphy (2010) and Anderson and Anderson (2012) examined the impact of accelerated terms on student achievement in quantitative-based classes. Murphy (2010) used a content-specific exam to compare the achievement of Master of Business Administration (MBA) students in 8-week and 16-week microeconomics classes and found a minimal difference in achievement between the two groups.

It was noted, however, that a student's ability to maintain an accelerated pace over time may be questionable. In a review of undergraduate students in an inferential statistics class, Anderson and Anderson (2012) found that a compressed semester with longer class meetings resulted in higher final exam scores and overall course grade point averages than students in non-accelerated inferential statistics courses. These findings indicate that an accelerated model can be successfully applied in face-to-face settings. Can the same be true of online classrooms?

The work of Diaz and Cartnal (2006), while dated, does offer a glimpse into the connection between academic term length and attrition and suggests that term length has been a significant factor in online learning for some time. Citing the literature that suggests the high dropout rates commonly seen in online education, Diaz and Cartnal (2006) offer the argument that dropout rates are not indicative of a student's lack of academic success. On the contrary, Diaz and Cartnal propose that adult learners may choose to drop a class as a strategic educational maneuver that would allow them to retake the class at a more opportune time without negatively impacting their GPA.

Recently, there has been a rise in the number of studies that address the issue of term length specifically in the online setting. Collins et al. (2013) note a paradigm shift in course development that is the result of changes in market demand. Through a mixed methods study, they sought to understand the experiences and expectations of preservice teachers completing coursework under a compressed model and found that some students take accelerated courses to complete a degree sooner and often for financial reasons (Collins et al., 2013). It was noted that many students entered accelerated courses with the expectation that the experience would be challenging, yet rewarding; however, some students preferred face-to-face instruction, but chose online learning because of family and time constraints (Collins et al., 2013).

Collins, Kang, Biniecki, and Favor (2015) also noted potential barriers to success in accelerated courses. In a study of an accelerated Master's degree program for military officers, the authors found that students who get behind in course work due to deployment, connectivity issues, or other life circumstances often struggle to catch up before the course ends (Collins et al., 2015). An accelerated program format does not work for every learner and for some military officers the pace is just too fast (Collins et al., 2015).

Rodrigue et al. (2016) studied student perceptions of term length in online business classes. The researchers' university offered both 8-week and 16-week term lengths for online courses, and faculty noted concerns not only with the practicality of teaching the same course over two different term lengths but also in the viability of teaching a quality course in just 8 weeks (Rodrigue et al., 2016). Using a five-point Likert scale, the researchers surveyed the 463 students enrolled in the program, receiving responses from 95 students (Rodrigue et al., 2016). When asked if they preferred one term length over the other, 90% of students responded that they preferred the 8-week term or a mix of 8-week and 16-week classes (Rodrigue et al., 2016). The researchers then asked about student preferences of term length for different academic content areas (specifically reading, writing, and mathematics), finding that fewer students chose an 8-week term for mathematics than for any other content type (Rodrigue et al., 2016). This finding is tremendously important because it sheds light on how students perceive time in relation to learning mathematics. The authors suggest that students feel challenged to complete their mathematics work in a shortened term and that "students perceive that having more time to process and apply mathematical concepts is beneficial to them" (Rodrigue et al., 2016, p. 227). It should be noted, however, that it is not made clear within the paper whether the 95 survey respondents actually took an online mathematics class, or if their responses were merely how they *thought* term length would impact their studies in a mathematics class.

Mensch (2013) has produced a very interesting descriptive study of the impact of term length on grades in online number-based classes, specifically 100 and 200 level accounting and mathematics/statistics classes. In comparing 5-week and 14-week terms, Mensch (2013) found that 54.5% of students in 5-week courses had final course grades of A or B, whereas only 45.7% of students in 14-week courses had such final grades. Interestingly, it was noted that students in the 14-week classes were twice as likely to withdraw and also had higher fail rates (Mensch, 2013). When compared to non-numeric courses, students in numeric-based courses had lower grades and lower retention rates (Mensch, 2013). These findings are quite relevant to the current study in that the students are taking lower level numeric-based courses. Mensch (2013) uses descriptive statistics for a preliminary review of the course data, but does not dig deep into the findings. What factors cause students in the shorter term length to have higher achievement? Are students going into the shorter term class with the expectation that they will need to work harder since, as Collins et al. (2013) noted, students often perceive accelerated classes as being a challenge? The first step in addressing this question is to determine the nature of the relation between achievement and term length. From there, a deeper examination of relevant factors, such as those that pertain to adult learners, can be completed.

Supporting Theories

This study is grounded in the adult learning theories of andragogy, self-directed learning, and transformational learning. As noted by the American Institutes for Research (2011), these three components undergird the knowledge base that supports adult learning. To empower the adult learner, Giannoukos, Besas, Galiropoulos, and Hioctour (2015) also support a multifaceted approach through the use of andragogy, social change, and transformative learning models.

Furthermore, according to Collins et al. (2013), adult learning theory underpins the success of accelerated learning programs.

Within the field of mathematics, Kleden and Adisucipto (2015) claim that students are highly dependent on teachers to identify learning goals. Given that the learning of mathematics encompasses precision, efficiency, and tenacity, Kleden and Adisucipto advocate for a self-learning approach in which students take ownership of their learning goals. The researchers recommend a metacognitive approach that supports a student's initiatives to learn.

Similarly, Rodrigues (2012) looked to the principles of andragogy to design and teach mathematics to adult learners. She believes that a student's self-concept shifts from being dependent on the teacher to becoming self-directed. To support her students as they learned mathematics, Rodrigues strove to increase their motivation through building self-esteem, lowering their math anxiety, and praising their efforts. Real-life applications of mathematics were also a foundation of the course. As a result of her students' successes, Rodrigues recommends incorporating adult learning principles into the design of similar courses.

Methodology

Since 2008, I have been teaching in the mathematics department at an online university. The university caters to adult learners, many of whom are active duty military, service professionals, or retired military members. The university hosts a comprehensive mathematics program, including a Bachelor of Science (B.S.) degree in mathematics with specializations in applied mathematics, operations research, and statistics. Even with a degree program in mathematics and degrees in other math-heavy disciplines such as engineering and astronomy, most students who enter the mathematics department at this university do so to complete their general education credits in mathematics. The vast majority of these students enroll in college algebra. Topics covered in college algebra include problem solving, basic linear equations, systems of equations, roots, and radicals. Students are presented with weekly lessons that include recorded lectures, slide shows, solved practice problems, and links to outside websites as additional resources. Students work sequentially through the lessons, participating in weekly interactive forums that require them to work through real-world problems and discuss the content as it relates to their daily lives. Connecting the course content with a student's daily life is an example of how adult learning theories, such as those noted in Rodrigues (2012), fit into the course framework. Furthermore, it is the hope that, through these activities, students will start to shift or transform their worldview of mathematics as a disconnected area of study to one that has true meaning and importance in their lives, thereby beginning the process of transformational learning (American Institutes for Research, 2011).

In addition to forums, there are also weekly homework assignments and tests, all of which are completed in MyMathLab, an online educational platform, that directly aligns with the course textbook. In MyMathLab, students have the opportunity to practice problems, complete assignments, and review a variety of multimedia-based resources. The resources are specific to each section of the textbook, making it very simple for students to locate resources on a given topic. For example, if a student is struggling with how to solve a system of linear equations using the graphing method, she can easily search for this topic in MyMathLab and find videos, slide shows, and sample problems. By allowing students to seek out and choose resources that meet their needs, MyMathLab supports self-directed learning (American Institutes for Research, 2011) and offers students the opportunity to take ownership of their learning goals (Kleden & Adisucipto, 2015), which is a foundational component of adult learning theories.

Upon enrolling in the course, students have the option of either a 16-week term or an 8-week term. Both tracks are identical in the content that is covered, where the distinguishing factor is strictly that of term length. It is worthy to note that, at the time of enrollment, students self-select into one of the two course term lengths. In addition, students do not take a placement test prior to enrolling, which leads to some students being ill-prepared to tackle the course objectives and expectations. In teaching college algebra for 9 years, I wondered what differences exist between the two term lengths. Specifically, is there a difference in achievement levels between the two term lengths?

Setting and Sample

To address the research question, data were pulled from 35 past sections of my college algebra class from Summer 2011 to Winter 2014. These included 7 sections of the 16-week term, to include 121 students, and 28 sections of the 8-week term, to include 691 students. Eight-week classes are offered more frequently at the university, hence the higher distribution of shorter term classes than longer term. Of the 887 total scores for the 8-week sample, 196 (or approximately 22%) were zeros. Scores of 0 were removed from the data set before analysis for two reasons. First, a score of 0 most likely indicates that the student did not complete the final exam. Second, including the scores of 0 in the analysis would pull the mean down in the analysis, thereby resulting in a biased mean. Of the 151 total scores for the 16-week sample, 30 (or approximately 20%) were zeros. Again, scores of 0 were removed from the data set before analysis.

Basic descriptive statistics were used to learn more about the two samples. In addition, the Mann–Whitney *U*-test was used to compare the final exam scores of students in the two groups.

Test Instrument

Students complete assignments using a popular third-party online mathematical software program, MyMathLab. This program is produced by the textbook company and aligns with the course content. The software is robust and contains a very large bank of mathematical problems. For the final exam, a set of 25 problems are randomly pulled for each student. The final exam is cumulative, covering all major topics from the course. Students log into the software program and are given 2.5 h to complete the exam.

Upon completion of the final exam, the software program produces a score. While generally accurate, the scoring does benefit from additional instructor review. The software does not allow for variances in the formatting of the final answer. Even though a formatting note accompanies each problem (such as "Write the answer as a simplified fraction."), not all students adhere to the recommendation. When this happens, a problem can be mathematically accurate but marked as incorrect by the scoring system. An example is when the student computes the slope using two points on a line. Since the slope formula itself is in fraction form, students often leave the final answer in fraction form, such as $m = 5/1$, rather than merely writing the slope as $m = 5$. It is up to the instructor to determine whether full or partial credit should be awarded. Having multiple formatting issues, such as these, can greatly impact a student's final score.

Reliability and Validity

Test reliability is the amount of measurement error in the scores yielded by a test, where a reliability of at least 0.80 is generally considered acceptable for use in research (Gall, Gall, & Borg, 2003). Since the final exam is algorithmically randomized for every student, each test is different which, according to Hodges and Kim (2010), means that traditional measures of reliability are impossible to determine. When developing the tests, the lead course instructor constructs the test parameters in MyMathLab. Chapter and section coverage, assignment difficulty levels (i.e. easy, moderate, hard, and very hard question types), and the estimated time to complete the test are all selected. Given these parameters, MyMathLab will generate a unique test for each student. If the lead course instructor chose to include four moderate problems from Chapter 3 of the text, for instance, then each test would include four randomly generated problems from Chapter 3 that are considered of moderate difficulty.

Validity refers to the appropriateness of inferences made from test scores (Gall et al., 2003). Content-related evidence, through assessment by a mathematics content expert, was used to demonstrate the validity of a sample test. Through a review of the course learning objectives, it was determined that the sample test questions appropriately measure student understanding of the course content.

Data Analysis and Findings

A histogram and basic descriptive statistics for the 8-week sample are presented in Figure 1. The final exam scores in the sample range from 12 to 100. The histogram shows that the data are skewed to the left with a mean score of 78.87.

The histogram and basic descriptive statistics for the 16-week sample are presented in Figure 2. The final exam scores in the sample range from 20 to 100. The histogram shows that the data are slightly skewed to the left with a mean score of 75.81.

Preliminary inspection of the two data sets reveals that the difference of the means is 3.06 points, where the mean score of the 8-week group is slightly higher than that of the 16-week group. The standard deviation of the 16-week group is slightly higher than that of the 8-week group, indicating that the scores of the 8-week group are more closely clustered around the mean.

Possible outliers were determined at three standard deviations above or below the mean. In the 8-week group, this range was from 26.046 to 131.694. Clearly, there were no scores above 100, and there were 12 scores that fell below 26 points. In the 16-week group, the ±3 standard deviation range was from 16.92 to 134.7. No scores fell outside of this range.

It was decided to keep the twelve scores from the 8-week and not remove them as outliers. This decision was made because the scores represent content knowledge on the exam. While low, in terms of relation to the mean, the scores are still meaningful and inform the research question.

Originally, I planned to use an independent samples *t*-test to compare the mean final exam scores of the two groups. In order to conduct an independent samples *t*-test, multiple assumptions must be met. These assumptions include having a dependent variable that is measured on a continuous scale; an independent variable that contains two categorical, independent groups; independence of observations; no significant outliers; for each group of the independent variable, the dependent variable should be approximately normally distributed; and homogeneity of variance must be present (Gall et al., 2003). Each of these assumptions will be discussed in detail below.

For this study, the independent variable was the term length, either 8 weeks or 16 weeks. The dependent variable was the score on the final exam. Scores ranged from 0 to 100 (where partial credit in varying amounts could be awarded for each problem) and, as such, were measured on a continuous scale. There exists independence of observations since there was no relation between the participants in the two groups nor in their test scores. Possible outliers were discussed above. Multiple methods were used to test for normality of the data, all of which are described below.

Figure 1: Histogram of 8-week sample

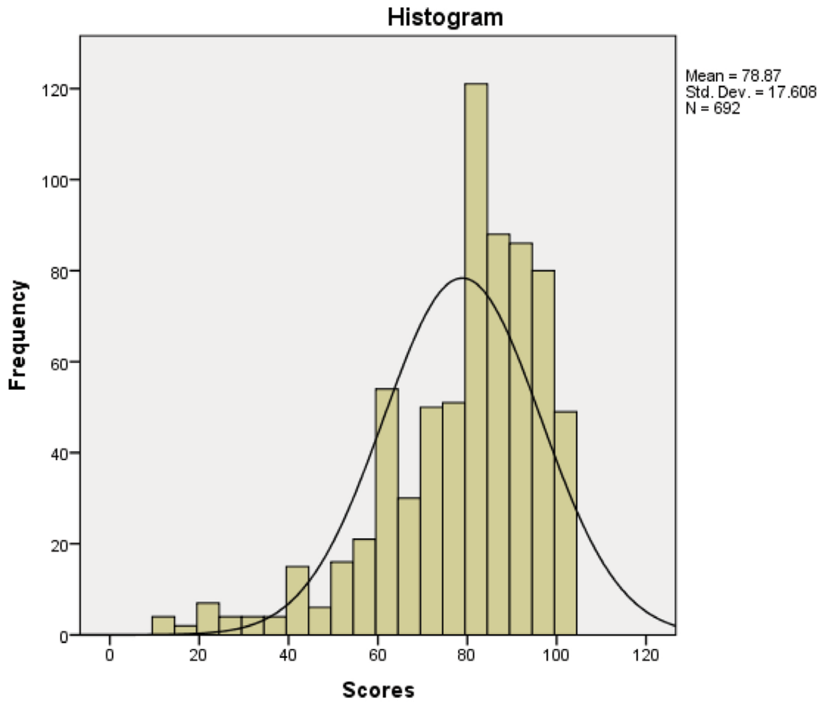
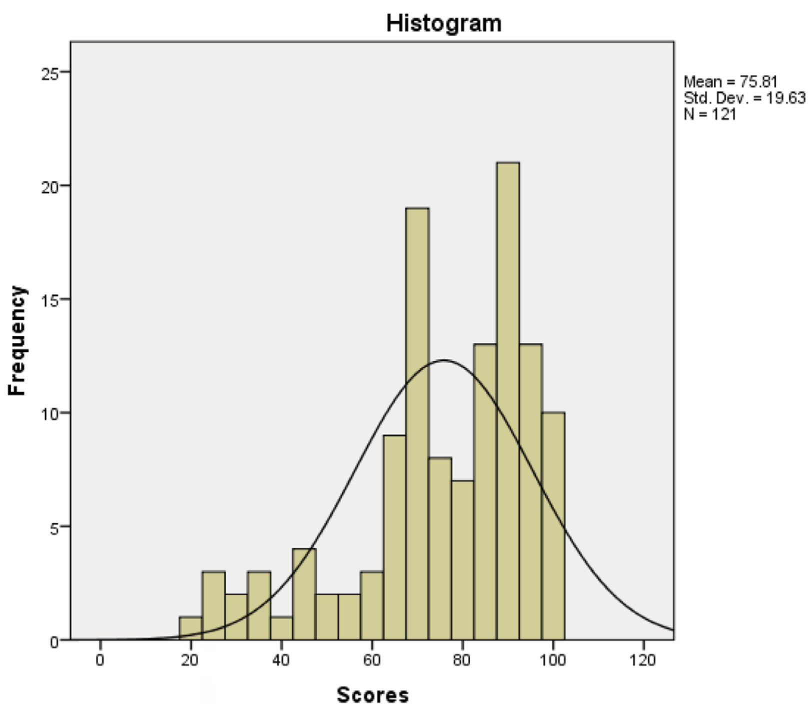


Figure 2: Histogram of 16-week sample



In Table 1, both the Kolmogorov–Smirnov and Shapiro–Wilk tests indicate that the sample data do not meet the normality assumption (Sig. <0.05).

Table 1: Tests of normality

Tests of Normality

Kolmogorov–Smirnov[a]			Shapiro–Wilk		
Statistic	df	Sig.	Statistic	df	Sig.
0.150	691	0.000	0.892	691	0.000
0.125	121	0.000	0.906	121	0.000

A visual inspection of the histograms shown in Figures 1 and 2 indicates that the data do not appear to follow the normal distribution. Furthermore, an examination of the skewness and kurtosis values can be used to determine if a sample approximates a normal distribution (Corder & Foreman, 2014). Table 2 shows the SPSS output table for the kurtosis and skewness of the test score data.

Table 2: Descriptive statistics

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. deviation	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
Score	812	12	100	78.50	17.803	−1.242	0.086	1.468	0.171
Valid *N* (listwise)	812								

Corder and Foreman (2014) indicate that the *z*-scores for the kurtosis and skewness must be manually computed. The *z*-score for kurtosis is found by subtracting zero from the kurtosis statistic in SPSS and dividing the result by the standard error.

$$z_k = \frac{K - 0}{\mathrm{SE}_k} = \frac{1.468 - 0}{0.171} = 8.585$$

The *z*-score for skewness is found by subtracting zero from the skewness statistic in SPSS and dividing the result by the standard error.

$$z_{Sk} = \frac{S_k - 0}{\mathrm{SE}_{Sk}} = \frac{-1.242 - 0}{0.086} = -14.442$$

In order for the test score data to meet the normality assumption, the *z*-score values must fall between −1.96 and +1.96 (with α = 0.05). Neither values falls within this range, so we can confirm that the sample data do not follow a normal distribution.

Since the data do not meet the assumption of normality for the parametric independent samples *t*-test, Corder and Foreman (2014) recommend turning to a non-parametric test. The non-parametric equivalent is the Mann–Whitney *U*-test. With this test, the samples are combined and rank-ordered together to see if the values are randomly mixed in the rank ordering or if they are clustered at opposite ends (Corder & Foreman, 2014). The null hypothesis is that there is no tendency of the ranks of one method to be systematically lower or higher than the other (Corder & Foreman, 2014). Table 3 shows the SPSS output for the Mann–Whitney *U*-test.

Table 3: Mann–Whitney *U*-test

Ranks

	Term	*N*	Mean rank	Sum of ranks
Score	0	691	411.69	284,481.00
	1	121	376.83	45,597.00
	Total	812		

Test Statistics[a]

	Score
Mann–Whitney *U*	38,216.000
Wilcoxon *W*	45,597.000
Z	−1.512
Asymp. Sig. (two-tailed)	0.131

Because the sig. value (0.131) is greater than the α value of 0.05, the null hypothesis fails to be rejected. This indicates that neither the 8-week term nor the 16-week term yields higher final exam scores.

To see if the inclusion of the outliers influenced the results, another Mann–Whitney *U*-test was performed with no outliers present. The results are presented in Table 4.

Table 4: Mann–Whitney *U*-test

Ranks

	Term	*N*	Mean rank	Sum of ranks
Score	0	679	406.84	276,245.00
	1	121	364.92	44,155.00
	Total	800		

Test Statistics[a]

	Score
Mann–Whitney *U*	36,774.000
Wilcoxon *W*	44,155.000
Z	−1.844
Asymp. Sig. (two-tailed)	.065

Again, the sig. value (0.065) is greater than the α value (0.05), which indicates that neither term length results in significantly higher final exam scores than the other. This aligns with the descriptive statistics, such that the mean final exam score in the 8-week class is slightly higher (78.87) than the mean final exam score in the 16-week class (75.81).

The purpose of this study was to determine if a significant difference in final exam scores exists between students in two different lengths of terms. Findings from the Mann–Whitney *U*-test indicate that there is not a statistically significant difference, which begs the question of why? What factors would lead to this finding? Furthermore, what are the implications for students and universities?

Perhaps, a key indicator is the fact that students self-select into the course, meaning that they choose whether to take a 16-week or 8-week class. An important consideration is *why* students choose one term over the other. Perhaps, it is due to their schedule, where one course fits in better (Diaz & Cartnal, 2006). Maybe it is because they perceive one term length to be a better fit for their current level of mathematical knowledge (Rodrigue, Fanguy, Soule, & Kleen, 2016). Particularly for those students who wait to take their math credits at the very end of their academic program, grit, or the perseverance to push forth and reach the long-term goal of graduating (Duckworth et al., 2007) may be a factor. The self-selection process, in and of itself, supports the adult learning theory ideas of Kleden and Adisucipto (2015), who encourage students to take ownership of their learning goals. Choosing a term length that best meets their needs can help students feel empowered to reach their learning objectives, but is there an ideal term length that best suits the needs of most students? For the students who chose the longer 16-week term, they may have done so because they felt that more time with the content would help in their understanding. As Bonk et al. (2015) and Collins et al. (2015) noted, there are time management concerns, especially with adult learners who also have career and family responsibilities. For some, trying to fit a large amount of content into a short period of time is unreasonable.

From an administration perspective, these findings show that the current trend of offering shorter class terms does not inhibit a student's development of mathematical content knowledge. It also has potential cost savings because it allows students to move through their academic programs at a faster pace without a loss in student content knowledge (Mensch, 2013).

There are, of course, potential downsides to accelerated courses. Many students are hesitant to take a shorter term class because they are not confident in their abilities to succeed in mathematics. Vilardi and Rice (2014) and Rodrigue et al. (2016) noted students' perceptions that more time is necessary to practice mathematics. Similarly, Collins et al. (2015) reported that the pace of an accelerated course is too fast for some students and that, if students get behind in their course work, it is hard to catch up. Perhaps, a longer term allows students to feel more relaxed and confident while learning the content. This would be an area for future study.

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