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Time is on my side….or is it? Time of day and achievement in an asynchronous learning environment

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Abstract:	Previous research on the effects of time of day (TOD) on cognitive performance implies that college students may be more successful if they schedule classes and tests in the afternoon and evening times, but in asynchronous learning environments, "class" and tests take place at any TOD (or night) a student might choose. The problem is that there may be a disadvantage for students choosing to take tests at a certain TOD. This study tested the effects of TOD on academic performance for undergraduate college students taking an asynchronous online Economics course. The findings show a significant negative correlation between TOD and assessment scores on tests taken between 16:01 and 22:00 hours within this asynchronous online course. Results of this research are intended to offer guidance to online students and instructors, as well as to instructional designers faced with setting deadlines and advising students on how to be successful when learning online. The major implication of this study is that online instructors, instructional designers and students should consider TOD as a factor affecting achievement in asynchronous online courses.

Time is on my side….or is it? Time of day and achievement in an asynchronous learning environment

Introduction

One draw of online learning is convenience. Students and instructors enjoy the flexibility offered by asynchronous online courses, which allow them to learn where and when it is convenient for them (Tallent-Runnels, et al., 2006). Learning Management Systems allow instructors to set deadlines for tests to be taken asynchronously, and thus students can take a test at any time of day so long as it is within the date range specified. Students could take a test at noon, or at one or four o'clock in the morning if they so choose, but would this matter? Does the time of day (TOD) students choose to take tests affect their performance? Previous research suggests that the optimal TOD for cognitive function (such as that utilized when taking academic tests) for young adults occurs in the afternoon and evening times (Allen, et al. 2008; May, et al. 1993). This research implies that college students may be more successful if they schedule classes and tests in the afternoon and evening time. In traditional classes all students typically take an exam at the same time, a time typically chosen by the instructor. But in asynchronous learning environments "class" and tests take place at any TOD (or night) a student might choose. The problem is that TOD may be a factor affecting student achievement in asynchronous learning environments. Could some online students be at a disadvantage simply because of when they choose to take a test? The purpose of this study is to determine if a relationship exists between TOD and achievement on assessments in an asynchronous learning environment.

Research Questions

1. What is the relationship between TOD and academic achievement on multiple-choice assessments within an asynchronous online course?

a. What achievement patterns can be found in the TOD students in asynchronous online classes choose to take tests?

b. What is the degree of the relationship between TOD and achievement within those achievement patterns?

c. Are TOD effects different depending on the level of cognitive ability being measured by the multiple choice test?

Justification

A recent survey of online educators in the United States revealed that 70.8% of academic leaders reported online learning is critical to their institution's long-term educational strategy (Allen & Seaman, 2014). Despite the clear emphasis on online learning in America's higher education system, there is little agreement within the research as to the effectiveness of online education versus learning in a traditional setting (Allen, et al., 2002; Anstine & Skidmore, 2005; Bergstrand & Savage, 2013; Botsch & Botsch, 2012; Clark, 1983; Coates, et al., 2004; Farinella, 2007; Lee & Choi, 2011; Nguyen, 2015; Russell, 1999). Many researchers join 44.6% of academic leaders who see retention as a greater problem in online courses than in traditional courses (Allen & Seaman, 2014). Forecasts indicate that online course offerings will continue to grow within American institutions of higher education (Allen & Seaman, 2014). Therefore it is important to identify factors contributing to student success and failure when learning online so that educators can, when possible, learn from them and mitigate issues that might prevent student success. TOD could be one factor affecting student success with online learning, and while there are bodies of research that could support recommendations for students on optimal TOD selection for learning, none of those studies specifically target online learners in asynchronous settings (Allen, et al., 2008; Callen, 1999; Carrell, et al., 2011).

This study represents a potentially important addition to existing research on TOD because there is little prior research on TOD effects in academic settings using academic measures. Moreover, our review of the literature found no other study which investigated the effects of TOD on achievement in online learning environments. Many of the studies on TOD effect involve data gathered from participant performance on abstract cognitive tests of ability within a clinical setting. Viewing the demonstration of cognitive function within a clinical setting as a constant that is transferrable to the natural learning environment is problematic as it fails to consider all of the extraneous factors which cannot be controlled in that student's natural environment. While testing TOD effects in the natural environment may risk internal validity, when a large sample size is used, external validity is expanded because extraneous factors are a reality in natural learning environments; especially for students taking asynchronous online courses. This study did not require participants to report to a laboratory setting but instead gathered data generated from students' natural environments wherein they normally participate in their online courses. Thus, findings of this study provide information on student behavior and performance in real-world asynchronous online settings. In addition, the abstract tests of cognitive ability involved in many of the existing studies were not related to content that was relevant to participants. Therefore, the cognitive tests themselves call into question the validity of those study results. Contrastingly, this study uses academic performance on subject matter-related tests to investigate TOD effects. This measure may yield results more generalizable to student performance in other courses and may therefore be preferable to tests of abstract cognitive reasoning.

Investigating the impact of TOD on achievement in online learning environments is important for determining if students taking tests at certain times of day are at a disadvantage. In addition to providing valuable information to students, findings of this study also offer guidance to online instructors and instructional designers faced with setting deadlines and advising students on how to be successful when learning online. This study is also intended as a call for further quantitative research into TOD effects on achievement in asynchronous settings. Results may also serve as a foundation of common experiences for future qualitative research on individual experiences with online learning and TOD taking human and specific environmental issues into consideration.

Literature

A great deal of the literature that exists on TOD is related to aging. These studies compare the effects of TOD on the cognitive abilities of young adults versus older adults (Anderson, et al., 1991; Borella, 2011; Bugg, et al., 2006; Colquhoun, 1971; Folkard, 1982; Folkard & Monk, 1979; Hasher, et al., 2002; Intons-Peterson, et al., 1998; Li, et al., 1998; Martin, et al., 2008; May, 1999; May, et al., 1993; May & Hasher, 1998; Yoon, et al., 2000). This body of literature is pertinent because of two important points that are established; younger adults are typically evening circadian arousal types (May 1993), and the synchrony effect; the idea that cognitive performance is optimal during peak circadian arousal periods (May & Hasher, 1998). The replicated findings that younger adults typically categorize as evening circadian arousal types (May, 1999) are very important to this study because they build the foundation for the assertions that young adults are at a disadvantage when expected to perform cognitive tasks at certain times of day (Allen, et al., 2008; Callan, 1999; Carrell, et al., 2011; Kirby, et al., 2011; Trockel, et al. 2000). The discovery, and later replication of the synchrony effect (May & Hasher, 1998), is also crucial to this study because if students experience peak cognitive performance during their peak circadian arousal period, and college students (who are typically younger adults) commonly experience peak circadian arousal during the evening hours, this means that students taking tests in asynchronous online courses might be at a disadvantage during hours other than evening hours.

There are fewer studies measuring the effects of TOD that are not related to aging. Some of this research is meant to influence school start times for high school students (Callan, 1999; Kirby, Maggi & D'Angiulli 2011; Kowalski & Allen, 1995; Link & Ancoli-Israel, 1995). This research asserts that high school students are disadvantaged by early morning schedules due to the evening circadian arousal patterns exhibited by adolescents (Kirby, Maggi and D'Angiulli, 2011). This body of research is relevant to this study because some researchers such as Carrell, et al. (2011), make the case that the research on high school start times can be generalized to college-aged students. However, there is also research intended to inform the start time of college classes (Allen, et al.; Trockel, et al., 2000; Carrell, et al., 2011). Findings from these studies indicate that working memory performance in college-aged students is affected by TOD effects, and that college students perform better on tests of fluency and processing speed in the afternoon and evening hours (Allen, et al. 2008).

Another area of literature that is related to TOD and academic achievement in asynchronous learning environments is learner control. Under learner control, students are given some degree of control with regard to pace, content, etc. (Hooper, 1992). Under program control the instructional program controls the content, pace, and other aspects of instruction (Hooper, 1992). Giving students the option to choose the TOD they take tests in an asynchronous learning environment is allowing them a level of learner control.

Although full of discrepancies and plagued by flawed research designs (Reeves, 1993), the research on learner control does indicate that providing some level of control to students can make them feel more competent and more intrinsically interested in content (deCharms, 1968; Lepper, 1985). However, other research indicates that students benefited from learner control only when they were informed about their own particular learning progress and advised on appropriate strategies for achieving mastery (Tennyson & Buttrey, 1980). The implications of the learner control literature is that more research is needed to clear up the discrepancies. Further, Schnackenberg and Sullivan (2000) note that the increasing popularity of internet-based instruction makes further research into learner control a necessity. This is “because of the very nature of the Internet and the World Wide Web, virtually all instructional sites have some degree of learner control. Therefore literal program control is not truly an option” (p. 34). It is important to note that this study is not an attempt to provide a basis for imposing program control. Instead, the results of this study are intended to provide guidance on TOD effects for students taking classes online, and for instructors and instructional designers who teach those classes.

Method

This research was performed on data which came from 84 undergraduate students taking an asynchronous online course, “Econ 2106: Principles of Microeconomics” (Econ 2106) administered during the fall 2015 semester at a large southeastern U.S. University through a learning management system called D2L/Brightspace. The average age of undergraduate students at this institution is 24. The course was set up to allow students access to all of the content at the beginning of the semester, but with specific weeks designated for each unit of content. A total of ten tests were scheduled weekly throughout the semester and administered through the LMS. Students had the ability to take tests at any time of day and on any day of the week, providing that they took the test prior to the deadline for a given unit, which was uniformly set at 10:00 PM on Friday evenings (Frost, 2015). TOD and assessment scores from all students taking the online course on all 10 tests given within that course were analyzed to determine if any achievement patterns in the times of day students took tests could be found. The results of the scatterplot and curve mapping from this analysis were used to split the data into groups based on TOD and achievement patterns. Next, simple regressions were performed on each set of split data to determine the degree of relationship between scores and TOD for each achievement pattern. The correlations were analyzed for each set of data and compared to determine if a relationship existed between TOD and assessment scores. Based on the literature related to TOD and young adults/college students, we expected to see a curvilinear relationship between test scores and TOD with higher scores for tests taken in the afternoon and early evening hours (Allen, et al., 2008; May, 1999).

In addition, each test that students took for the course was analyzed to determine the level of cognitive skill required by each test item. The vast majority of items were taken from two published test banks; the Test of Understanding of College Economics (TUCE-4) (Walstad & Rebeck, 2008), and the instructor's resource folder for *Principles of Microeconomics* by Mateer and Coppock (2014). The remaining questions were composed by the instructor. The work of identifying the cognitive complexity of test items had already been accomplished for the questions that were taken from existing sources. The TUCE-4 uses a modified version of Bloom's taxonomy (1956) to categorize questions by cognitive complexity into three categories (Walstad & Rebeck, 2008). Recognition and Understanding (RU), encompasses the lowest two levels within Bloom's Taxonomy. Explicit Application (EA) includes the next two levels within Bloom's Taxonomy. Implicit Application (IA) encompasses the highest levels of complexity. All test items for the TUCE-4 were assigned a numeric score based on their classification as RU

(1), EA (2) or IA (3). The test bank for *Principles of Microeconomics* (Mateer & Coppock, 2014) ranks the cognitive level of test questions based strictly on Bloom's Taxonomy (1956). These rankings were converted to numeric rankings based on the rating criteria used by the TUCE-4. In addition, complexity for the instructor-created test items were determined using the same modified version of Bloom's taxonomy used for the TUCE-4 (Walstad & Rebeck, 2008), then converted to numeric scores. Finally, mean complexity scores on a scale of 1-3 were determined for each test by analyzing the individual test item scores within each test.

Finally, SPSS was used to perform a hierarchical multiple regression controlling for test complexity using the complexity scores determined for each test. Since it can naturally be assumed that the complexity of any assessment would affect scores, the goal of this statistical test was to determine how much variance could be attributed to TOD effects after controlling for test complexity.

Results

First, it was necessary to test the linearity of the relationship between TOD and assessment scores. SPSS was used to perform a linear regression curve estimation using score as the dependent variable and TOD as the independent variable. The resulting scatterplot is shown (see Figure 1). Note that TOD is shown based on the 24-hour clock. The linear fit line represents the linear model. The jagged line represents the observed data.

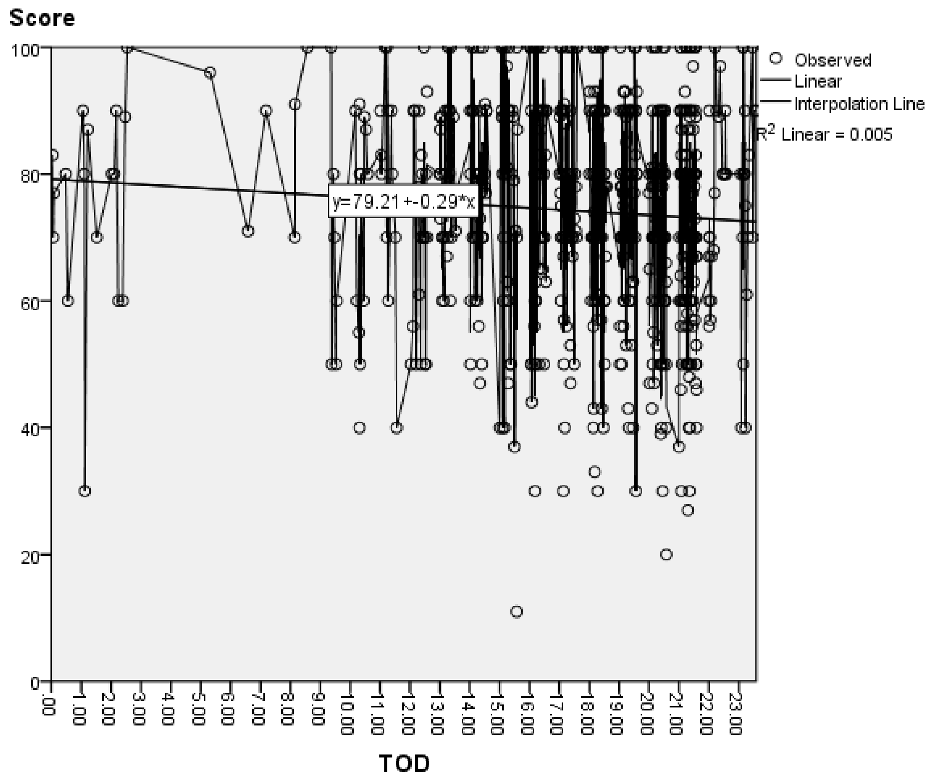

Figure 1. Linear Regression Curve Estimation between Score and TOD

While these lines clearly do not mirror each other, the non-linear relationship is not evident from the scatterplot. However, the *F*-test did not produce a significant result, *F* (1, 678) = 3.572, *p* = .059. This means that the linear model is a poor fit for determining the relationship between TOD and assessment scores for this data (see Table 1).

Table 1

Linear Regression Curve Estimation

Group	F	df1	df2	Sig.
All	3.572	1	678	.059

While only slightly non-linear, the relationship between TOD and assessment scores cannot be determined using correlation. However, splitting the data into groups in which these variables do exhibit a linear relationship would make it possible to determine the degree of correlation. In order to rationalize any split in the data, a locally weighted polynomial regression (LOESS) line was added to a scatterplot of the TOD and assessment score data, and compared with the linear regression line (see Figure 2).

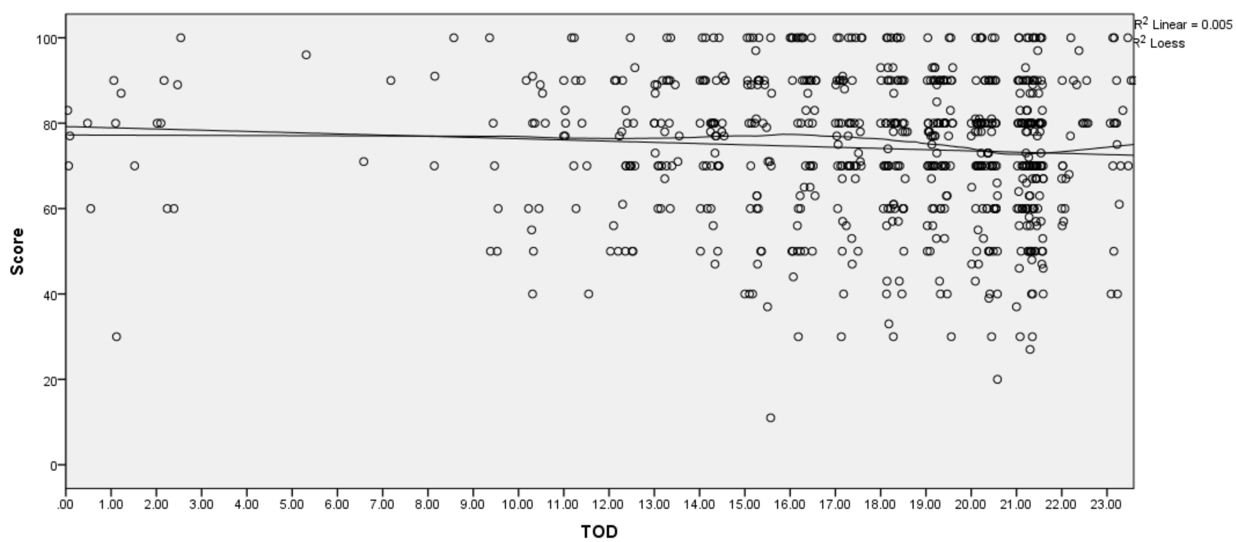

Figure 2. Linear Regression versus LOESS TOD and Assessment Scores

LOESS was used for this study because of the ability it affords researchers to determine the local variation in the data point by point, making it easier to segment that data based on local variation versus the global variation shown in a linear regression model (NIST, 4.1.4.4). As shown in Figure 2, the LOESS line curves to intersect with the linear regression line at 7:00 hours. It then curves again at 11:00 hours, 16:00 hours, and 22:00 hours. These curves in the LOESS line indicate the rise and fall of mean assessment scores across time. Since the goal of introducing the LOESS line was to split the data into groups which could exhibit a linear relationship, thus showing achievement patterns, the curves were used to split the scores based on the TOD tests were taken. Therefore, the data set was split into 5 groups (see Table 2). Note that time periods are not equal segments because they are based on the differences between the LOESS line and the linear regression line instead of on hourly increments.

Table 2

Large Data Set Split by TOD

Group	TOD
1	0.00 – 7:00 hours
2	7:01 – 11:00 hours
3	11:01 – 16:00 hours
4	16:01 – 22:00 hours
5	22:01 – 23:59 hours

Next, SPSS was used to perform linear regression curve estimations on each set of split data using score as the dependent variable and TOD as the independent variable. This test revealed no significant linear relationship between TOD and assessment scores for groups 1, 2, 3 and 5 with alpha set at .05. However, a significant linear relationship between TOD and assessment scores was determined for tests in this data set taken between 16:01 and 22:00 hours (see Table 3).

Table 3

Linear Regression Curve Estimations on Split Data

Group	F	df1	df2	Sig.
1	.555	1	17	.466
2	.811	1	22	.378

3	.007	1	139	.932
4	6.443	1	457	.011*
5	.227	1	35	.637

*Significant at α = .05

Since TOD and assessment scores only had a significant linear relationship between 16:01 and 22:00 hours, that is the only TOD that could be investigated using the Pearson *r* correlation coefficient. This test revealed a slight negative correlation between the two variables with lower scores associated with later TOD (r = -.118, n = 459, p = .011). Mean scores for tests taken later in this time period were significantly lower than mean scores for tests taken earlier in the time period.

In order to mitigate any extraneous factors related to the tests themselves, we wanted to see if the complexity of tests played a role in any TOD effects that were significant. Table 4 shows the cognitive complexity scores on a scale of 1-3 for each test given in Econ 2106.

Table 4

Test Complexity Econ 2106

Test	Complexity
Exam 1	1.46
Exam 2	1.44
Exam 3	1.44
Exam 4	1.80
Exam 5	1.20
Exam 6	1.40
Exam 7	1.60
Exam 8	1.33
Final Exam 1	1.48
Final Exam 2	1.53

Since TOD effects were only significant during the TOD between 16:01 and 22:00 hours, scores, TOD and test complexity from that TOD only were used to perform a hierarchical multiple regression in order to assess the TOD effects on assessment scores, after controlling for the influence of test complexity. Test complexity was entered first, explaining 1.2% of the variance in assessment score, F (1, 457) = 5.35, p = .021. Next, both TOD and test complexity were entered into the statistical model, and were found to explain 2.5% of the variance in assessment score, F (2, 456) = 5.84, p = .003. TOD was found to account for 1.3% of the total variance in score after controlling for test complexity, R squared change = .013, F change (1, 456) = 6.28, p = .013. In the final model between the hours of 16:01 and 22:00, both TOD and test complexity were found to have a statistically significant effect on assessment scores, with test complexity only recording a slightly higher beta value (*beta* = -.105, p = .023) than TOD (*beta* = -.116, p = .013). Tables 5 and 6 show the results and effect size for this hierarchical multiple regression.

Table 5

Hierarchical Multiple Regression Scores, TOD Controlling for Test Complexity

Model	R Square	F	R Square Change	df1	df2	Sig. F Change
1	.012	5.350	.012	1	457	.021
2	.025	5.844	.013	1	456	.013

Table 6

Effect Size Hierarchical Multiple Regression Scores, TOD Controlling for Test Complexity

	Beta	Sig.
Test Complexity	-.105	.023
TOD	-.116	.013

Discussion

This study investigated the relationship between TOD and academic achievement on multiple choice assessments given within an asynchronous online course. The findings show that when test scores from this data set were examined over a 24-hour time period a linear relationship did not exist between these two variables. However, a curvilinear relationship was confirmed, allowing for TOD to be segmented into achievement patterns for students in this asynchronous class. Through analyzing these TOD and assessment scores within these achievement patterns, a significant TOD effect was found for students taking tests between the hours of 16:01 and 22:00, F (1, 457) = 6.44, p = .011. Although correlation does not equal causation, a slight negative correlation (r = -.118, n = 459, p = .011) between TOD and assessment scores was found within this statistically significant achievement pattern indicating that Econ 2106 students taking tests online between 16:01 and 22:00 hours could expect as much as 1.4% (R^2 = .014) negative effect on their grade the later they took the test during this time period.

We wanted to determine the magnitude of the TOD effect when extraneous factors related to the tests themselves were controlled. It is interesting to note is that once test complexity for this TOD group was statistically controlled, TOD still accounted for 1.3% of the total variance in score between 16:01 and 22:00 hours, F change (1, 456) = 6.28, p = .013. Thus, there was a significant TOD effect for students taking tests between 16:01 and 22:00 hours within this asynchronous online learning environment (*beta* = -.116, p = .013). In addition, the effect size for test complexity was comparable to that of TOD. Since the standard deviation for the mean (M = 73.26) of all tests taken between 16:01 and 22:00 hours was 16.90, when analyzed with the effect size, TOD was found to affect test scores by as much as -1.96 points.

Test complexity was found to affect test scores by as much as -1.77 points (*beta* = -.105, *p* = .023). This means that there is not only a TOD effect found for students taking this asynchronous course during this time period, but that the TOD effect is comparable to any effect that test complexity would have on assessment scores.

When placed into the larger context of asynchronous online learning and student achievement, these findings have the following implications for those teaching online courses, as well as those taking online courses:

Students, instructors and instructional designers should consider TOD as a factor affecting achievement in asynchronous learning environments. The finding of a significant TOD effect for these students taking tests between 16:01 and 22:00 hours is magnified because of the 680 total assessment scores from 84 students used, 459 of those scores were achieved between 16:01 and 22:00 hours. Whether out of necessity or preference, students in this asynchronous online course chose to take tests between 16:01 and 22:00 hours at a greater rate than in the other times of day. If this test-taking pattern is indicative of patterns in other asynchronous courses, it is important to consider the role TOD may play in achievement during this time period. It is also important to make students aware that TOD effects may impact their achievement in asynchronous courses.

We are not advocating for program control over the TOD students take tests in asynchronous learning environments. To place limits on the accessibility of online education would serve to limit the opportunity that online education brings to those who rely on that convenience. Instead, educators need to make students aware that TOD could play a role in their achievement and let them decide for themselves if they want to adapt the time they take tests. Providing students the research findings on TOD effects would allow them to reflect on their own learning and cognitive ability, and help them foster an awareness of any limitations that TOD may place on their individual ability to achieve success when learning online. In this way learners can work to adapt their behavior and strategies to fit their own learning needs.

The implication that TOD should be considered as a factor affecting student achievement in asynchronous online courses is meaningful because it represents something new in the research. One gap noted in the research on TOD and academic achievement is that few studies research TOD effects within students' natural learning environments. Further, we did not find any research on TOD effects within asynchronous online learning environments. The finding that TOD effects were statistically significant in this asynchronous online learning environment between the hours of 16:01 to 22:00, establishes a new area of research on TOD and best practices in online education. In addition, the number of scores analyzed for the non-significant time segments were all lower (0:00 to 7:00, N = 19; 7:01 to 11:00, N = 24; 11:01 to 16:00, N = 141; 22:01 to 23:49, N = 37) than the number of scores on tests taken between 16:01 and 22:00 hours that were analyzed. Perhaps a relationship between TOD and assessment achievement in asynchronous courses could be found with larger numbers analyzed for each TOD. Now that it is established that TOD should be considered as a factor affecting student achievement in asynchronous online courses, further research is needed.

While young adults may perform better on asynchronous assessments when taken during evening hours, this positive TOD effect may eventually decline the later students choose to take tests. The slight negative correlation (r = -.118, n = 459, p = .011) found in this data between TOD and assessment scores for tests taken between 16:01 and 22:00 hours would indicate that the later students took tests during this time period, the lower their scores were. This means that advising college-aged students to take tests in the evening may not be effective unless we specify what we mean by ‘evening.’ Upon examining the difference between the linear regression and the LOESS lines for the large data set in this study (see Figure 2), we see that achievement peaks at about 16:01 hours, then steadily declines until 22:00 hours. Since this is the only TOD where statistical significance was found, we can only objectively discuss this time period. Therefore, advising college-aged students to take tests earlier in the evening as opposed to later in the evening would have the best probability of ensuring success.

We were unable to find any TOD research that tested students on a 24-hour scale. The studies in the body of literature on TOD test students at specific times. Typically morning times of testing were between 8 AM and 10 AM (8:00 to 10:00 hours), afternoon testing was between 12:00 PM and 5:00 PM (12:00 to 17:00 hours), and evening testing times ranged from 5:00 PM to 8:00 PM (17:00 to 20:00 hours) (Allen, et al., and 2008; Anderson, et al., 1991; Bennett, et al., 2008; Borella, 2011; Callan, 1999; May, et al., 1993; May, 1999). For this study, examining a larger range of time was necessary in order to adequately study TOD effects for asynchronous online learners who are given much broader parameters of time to take tests in their natural learning environment. While our study does not involve repeated measures testing like those by Anderson (1991) and Allen (2008), these findings do suggest a decline in evening performance beyond 20:00 hours among students taking tests later in the day. The implication for these findings is specific to asynchronous online courses, because while it is possible that face-to-face courses could be testing as late as 22:00 hours, it is unlikely. Further, the implication that any positive TOD effects may diminish by 22:00 hours is an important contribution to TOD research because it goes beyond the existing times tested in prior literature. Additional research is needed to determine the point in time for which score decline can be expected.

We can naturally assume that the cognitive complexity of an assessment will affect achievement, however we cannot ignore that TOD could play a comparable role when tests are taken in an asynchronous learning environment. This is relevant to student success in online learning because of the comparison to test complexity. While instructors may be able to advise students on optimal times to take tests, without imposing program control, the onus for heeding this advice is on the student. Equating TOD impact to any effect test complexity may have on their achievement could serve to put this idea into perspective for students and motivate them to adapt their test taking time accordingly. Tennyson and Buttrey (1980) found that students benefit most from learner control when offered meaningful guidance. Any TOD recommendations that can be made from this study are made more meaningful to students by placing them into perspective.

We have found many studies that test specific cognitive competencies using abstract assessments, and that report TOD effects on those specific competencies. However, we have not found research measuring the complexity of academic tests, which involve several cognitive competencies at the same time, and determining the variance in test achievement based on TOD and cognitive complexity. The results of this study will allow students to place TOD effects into a relatable perspective, and provide online instructors advising students on TOD selection with an appropriate framework of comparison to motivate students to heed advice.

Limitations

One limitation of this study is that in addition to TOD effects, confounding variables such as the number of hours students study for the test, the individual abilities of each student, etc. could affect the scores on the tests. To help mitigate the results of confounding variables, test complexity was taken into consideration according to the variance it contributes. One limitation to this is that 5 test questions did not have publisher-determined complexity levels, and were instead evaluated by a panel of Ph.D. students to determine complexity. While these Ph.D. students all had experience teaching, were familiar with Bloom's Taxonomy and had been instructed on and calibrated for determining the TUCE-4 rating system, they were not necessarily familiar with the Economics-related content. However, these questions represent a small percentage of the total test questions used throughout the 10 tests.

Another limitation of this study is that the deadlines for completing tests were set at 10:00 PM (22:00 hours) (Frost, 2015). Therefore, on the last day of the availability period, the time span for this study only included the hours between 0:00 and 22:00. This also means that there were no test scores from the 22:01 to 23:59 hour achievement period that were taken on the day of the test deadline. However, all tests for this course were available on the first day of the semester. There were suggested weeks to take each test, with deadlines set for the end of that week. Therefore theoretically, students could have taken all 10 tests during the first week of class, and besides the deadline days all other days during the test availability period include data from times spanning 0:00 to 23:59 hours. Despite this, the 10:00 PM deadline might have been a factor in the significance of the achievement pattern between 16:01 to 22:00 hours. For all tests given in Econ 2106, 70.4% were taken on the day of the deadline. Of those tests that were taken on the day of the deadline, 19.9% were completed between 21:00 and 22:00 hours. If the instructor had set the deadline later, perhaps the significant TOD would change. In addition, this may indicate that other factors such as procrastination may be at play besides TOD. Further quantitative and qualitative research is needed to determine how additional factors contribute to decreased performance on tests between 16:01 and 22:00 hours.

The 19.9% of scores on tests which were taken within 1 hour of the deadline may have also been affected by the testing environment. These 10:00 PM deadlines fell on Friday nights (22:00 hours) (Frost, 2015). This day and time may have made testing more difficult for these young adults. College students who have been in classes all week tend often use weekend evenings to relax and celebrate the end of the week. With no early classes to attend, they may celebrate into the late evening hours and early morning hours. The sounds of celebration could be distracting for students who live in dorms or even for students who live off campus with fellow college students as roommates. By 10:00 PM on any given Friday, weekend celebration would be in full swing for college students. This confounding factor could have an effect on test scores for students who chose to test just before the deadline posted on the syllabus. Further research would be needed to rule this confounding variable out.

While time measurement for this study was based on a continuum, time for each day started at 0:00 hours and ended at 23:59 hours. This may have created an artificial distinction between times, but the choice to start time and end time at these points was made because the 24-hour clock establishes this precedent. It would be interesting to conduct future research including time as a continuum using different start times and end times in order to explore the relationship between TOD and achievement in asynchronous learning environments. Specifically, we would like to determine if there is a relationship between TOD and academic achievement during the late night hours; perhaps between 23:00 hours and 4:00 hours. However, that type of study would not be possible with the data used for this study because so few students took test during these times.

Suggestions for Future Research

In addition to further quantitative research to confirm the generalizability and mitigate the limitations of these findings on TOD effects in asynchronous online courses, further quantitative, as well as qualitative research is needed to consider the role of procrastination in TOD selection and determine if maladaptive procrastination contributes to TOD effects. While procrastination was not the focus of this study, quantitative evidence did reveal that a majority of the test scores from this course were the result of students taking the tests on the day of the deadline. This is objective evidence that students were putting off taking tests, but the question of whether students were procrastinating cannot be answered from this data alone. We suspect a link between TOD effects in asynchronous online courses and the negative effects associated with maladaptive procrastination. However, the results of this study cannot be linked to procrastination because we do not know what motivated students to choose the time they took tests. Further mixed methods research is needed to replicate the quantitative results of this study and then explore the factors that play a role in the time students choose to take tests in asynchronous learning environments.

Conclusion

Time of Day played a small but significant role in student scores on assessments in an asynchronous online class. This role was equivalent in size to that played by test-item complexity. As higher education institutions move toward a more data-driven approach to educational attainment, it is important that we identify factors that can contribute to this attainment. This study seeks to begin that process by examining one of the myriad factors now accessible to data analytics. We intend it to be a small, but important first step in establishing a catalog of meaningful elements which can be used to inform a big data analysis of best practices in online education. We are at the beginning of a period in which a mass customization of educational experience maybe possible. Each learner may have a personal learning environment informed by learning analytics and driven by some level of artificial intelligence. It is our hope that this study may be one of the building blocks to achieving that future.

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