Time Management Factors for Success in Higher Education

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Accessibility
Time Management Factors in Higher Education Success:
An Exploration of Self-Report and Learning Management System Predictors in
Continuing- and First-Generation Students

Dorothy Bisbee

A Thesis in the Field of Psychology
for the Degree of Master of Liberal Arts in Extension Studies

Harvard University

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For this exploratory study, 109 adult students (73.4% female) completed an online survey with measures of time management behavior and college wellbeing during the fall semester. Students were in 10 courses at a continuing education school within a large northeastern U.S. university. On a follow-up survey, 87 reported their grades and answered additional questions about time use and management. Factor analysis of self-report measures identified a three-factor structure for time management: Satisfaction with Time Use, Monitoring and Evaluating, and Planning and Prioritizing. Satisfaction with Time Use best predicted college wellbeing on the College Student Subjective Wellbeing Scale (CSSWQ, Renshaw & Boligno, 2016). Number of time management tools used negatively predicted grades and course completion, and the Mechanics dimension of the Time Management Behavior Scale (Macan, Shahani, Dipboye & Phillips, 1990) positively predicted grades and course completion. Each student’s activity on the course learning management system (LMS) was collected, de-identified, and used to show study times of day. Study times of day did not emerge as significant predictors. Some differences between first-and second-generation college students were seen: first-gen students worked more hours per week, on average, than their peers, and fewer of them got at least seven hours of sleep per night. Still, their grades and course completion rates were similar to their peers’. Satisfaction with Time Use was a better predictor of grades and course completion than Mechanics for first-generation students. Directions for future research are identified.
Dedication

To Yogi and Phoenix, for your patience and for who you are.
Acknowledgments

Jenny Gutbezahl went beyond the call as my Research Director. Her humor, patience, wisdom, empathy, teaching skills, incisive editorial suggestions, and ability to be real were fundamental to this thesis.

I also especially want to acknowledge Shelley Carson, the catalyst for my research work. Back in 2013, before I was her student or even enrolled at Harvard Extension, Dr. Carson offered to help with my first research study. She did the lion’s share of design and analysis in that study, teaching me along the way, and has been a role model, mentor and inspiration in and out of the classroom.

For the current study, Andy Engelward, Principal Investigator, volunteered many hours of logistics and brainstorming; his optimism, kindness and problem solving revived the study at times when it seemed all was lost. Dante Spetter, my Research Advisor, guided me through the thesis proposal process from early on, and I am grateful for her clarity, experience and careful format review of this thesis.

Glenn Lopez of Harvard’s Office of the Vice Provost for Advances in Learning (VPAL), collected, de-identified and prepped an entire semester of data for this study. I had no idea how much I was asking him when I requested his help. Ilia Rushkin, also at VPAL, for shared ideas and support.

Thanks to Helen Consiglio and Leslie Gindro at Regis College for their generous advice, and to Chuck Houston at Harvard Extension for listening and advising.
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Chapter I

Introduction

This thesis is an exploration of the relationship between time management behavior and adult student success, and a look at whether time management measures need updating for today’s online world. Participants were 109 students taking online or hybrid courses at a large continuing education school associated with a university in the U.S. northeast region. The study built on past time management research by including predictors that come from today’s online world, and exploring differences between first- and continuing-generation students.

Success was measured by final grades, sense of wellbeing, and course completion. Predictors came from self-report, using old and new questions, and data from Canvas extracted throughout the semester.

This was an exploratory study, with no specific a priori hypotheses as to which predictors would show the strongest association, or whether they would differ for first-generation students. Factor analysis, multiple linear regression, bivariate correlation and other techniques were used to explore the relationships between time management predictors, and academic success. Because the sample size was smaller than expected, and the variance in grades and course outcomes was minimal, there was insufficient power to detect smaller effects. However, some significant findings about predictors of college wellbeing, grades and course completion emerged, and areas for future research were identified.
Definition of Terms

*College wellbeing:* academic satisfaction, school connectedness, self-efficacy, and college gratitude, as measured by the College Student Subjective Wellbeing Scale (Renshaw & Bolognino, 2014; Renshaw, 2016)

*First-generation:* having no parent or guardian who has attended college

*Learning analytics:* study of large-scale data to describe student behavior and improve education

*Learning Management System (LMS):* an online platform that links students to course resources and logs student activity

*Procrastination:* delaying action despite knowing the delay will sabotage goals

*Time management:* the use of habits, strategies, and deliberate behaviors for optimal allocation of time to achieve goals or preferences

Background

The best self-report time management measures date to the early 1990’s, before education went online, so the findings may not generalize to today’s students. Also, the academic support strategies offered to students are often not evidence-based (McCabe, 2018).

The growing field of learning analytics may offer some help. Researchers are exploring how to use LMS log data to inform students, instructors, and academic support staff. While this is promising, most of the studies have used aggregated data, and few
have combined individual student data with log data, so it is unclear how learning analytics can best complement or supplant surveys.

This study explores how self-report and LMS data may complement one another in identifying time management predictors of academic success. The background discusses past research into time management, how it relates to higher education in the 21st century, and what old and new instruments are available to measure it. Popular and well-validated time management measures like Macan’s Time Management Behavior Scale are discussed, along with recent research in the growing field of learning analytics. Both methods’ predictive value for student success is reviewed.

Time Management in Higher Education

It is easy to find advice on time management. In April 2016, a Google search for the words “time management for students” (no quote marks were used) yielded 57.9 million hits returned in half a second. An identical search in March 2019 yielded 1.67 billion hits in less than half a second. It is also easy to find time management tools. Everything is available on students’ phones and laptops: the time of day, the date, calendars, to-do lists, planners, project management apps, apps to track time on the Internet, apps to block access to certain sites at chosen times of day, apps to focus, apps to track sleep, and so on. With all these resources, it can be difficult to disconnect from the Internet. Researching, evaluating and implementing time management advice can be a form of procrastination in itself.

Most colleges and universities offer resources to assist students with time management. The results of a November 2017 Google search for “college academic support services” followed by search for “time management” in the first ten colleges that
appeared, showed all but one college offering time management advice and/or support in the form of workshops or tip sheets (Appendix A). Several colleges offered time management as a full day’s topic in a first-year seminar, and one even offered a certificate in productivity and time management. McCabe (2018) surveyed academic support centers at 77 U.S. colleges. When she asked center directors for their top three strategy recommendations, 58% of the responses related to time management (McCabe, 2018). Based on a study of 83 freshmen on academic warning or probation at a U.S. college, Balduf (2009) recommended that orientations for all college freshmen include time management strategies.

Students are initially referred for academic support when instructors, or the students themselves, report that they are struggling. Academic coaches, learning specialists, tutors, advisors and others help students with academic skills one-on-one, in groups, and by offering information on academic support web pages. While tutors focus on subject-specific guidance, academic coaches and learning specialists offer more general assistance. They may help students with time management and general organization skills, offer strategies for better reading, writing, studying, and test taking, and encourage students to improve sleep and exercise habits, manage stress and seek better life balance. In the end, everything relates back to time management.

Changing Demographics

The demographic profile of higher education institutions has changed a lot since the start of the new Millennium. Student bodies are more diverse in terms of race/ethnicity and age. For example, nearly 70% U.S. postsecondary students were White in the year 2000. By 2016, that figure had dropped below 57% (U.S. Department
of Education, 2017a). Enrollment of students aged 25 to 34 years old increased 35% from 2000 to 2014, and may increase another 16% by 2025 (Hussar & Bailey, 2016). For students aged 35 and older, enrollment increased 23% from 2000 to 2014, and may increase another 20% by 2025 (Hussar & Bailey).

More than half of today’s college students are the first in their families to attend college (Fishman, Lidgate, Tutak, & Singh, 2017). First-generation students in the current study worked an average of 13 hours a week more than their peers, and spent about 1.5 hours more each week caring for dependents. With an average of two hours more per day of non-academic commitments than their peers, these students are at a time management disadvantage. There is little research on how time management may differ for these students, and this study was designed partly to help fill the gap.

Competing Responsibilities

Most of today’s college students have non-academic responsibilities that compete for their time, such as employment and caring for dependents (Fishman et al., 2017). As of 2015, 43% of full-time, and 78% of part-time, U.S. college students were employed (U.S. Department of Education, 2017b). 10.4% of full-time students were also employed full-time, and 45% part-time students were employed full-time. The current study was at a continuing education school, and 53.4%, a bit higher than the national average, of the study participants were juggling full-time work with school.

The burden a job puts on a student’s time management is even bigger when the hours are unpredictable. Work schedules may change every week and be distributed on short notice. Also, work can impede sleep. Some students work all night, and go to their
classes in the morning. Situations like this can make traditional tips like “go to bed at the same time every night” and “don’t take naps” useless.

Mental Health and Wellbeing

Rates of stress, depression and anxiety among college students are increasing (Beiter et al., 2015). Together, two reports from an ongoing study the Higher Education Research Institute (HERI) show how anxiety can skyrocket during the first year of college. In Fall 2016, about 12% of over 15,000 entering freshmen participating in the HERI study reported having felt anxious “frequently or occasionally” in the past year (Eagan, Stolzenberg, Simmerman, Aragon, Whang, Sayson, & Rios-Aguilar, 2017). By Spring 2017, 38.6% of over 8,000 freshmen reported having felt anxious “frequently” since entering college (Couch, 2018). That is over three times the fall rate, and half of the students in the spring cohort had also participated in the fall study.

High rates of postsecondary student mental health problems are probably not limited to the United States. Younes et al. (2016) reported a study of 600 medical, dental and pharmacy students in Beirut. About one in ten students had clinically significant insomnia and depression, about half were experiencing moderate to extremely severe stress, and over a third were experiencing moderate to extremely severe anxiety. The researchers found strong correlations between student mental health and potential Internet addiction. While this sample may not have been representative of U.S. college students, the degree of the problem is alarming. Also, now that so much education is online, students can take the same class from all over the world. Participants in the current study represented regions from Asia to Europe to Australia, in addition to the Americas.
Unfortunately, students with mental health concerns often do not seek counseling. In a recent worldwide study of 1,572 college students, about 20% reported mental health disorders over a 12-month period, but only 16.4% of that 20% received even minimally adequate mental health treatment (Auerbach et al., 2016). While the treatment rate in high-income countries such as the United States was slightly better, at 21.3% (Auerbach et al.), nearly 80% of students with significant mental health disorders were not receiving adequate treatment. In the Spring 2017 HERI survey, of the 23.1% of students reporting “below average or extremely low” mental health in their first year of college, less than half said they had sought individual counseling (Couch, 2018).

The latest report on a large annual survey of college counseling centers also shows that anxiety and depression rates for U.S. college students rose quite steadily from 2013 to 2017 (Center for Collegiate Mental Health, January 2019). In 2018, over 60% of counseling centers listed anxiety as their clients’ main concern. For depression, the 2018 rate was about 50%. The study stated that only 18.4% of students reported having sought counseling since starting college.

It is likely that stress is a factor in depression and other mood disorders (van Praag, 2004). Better time management may help prevent or reduce stress (e.g., Feather & Bond, 1988; Häfner, Stock, Pinneker, & Ströhle, 2014; Häfner, Stock & Oberst, 2015; Macan, Shahani, Dipboye & Phillips, 1990; and Misra & McKean, 2000). By helping students with time management, academic support professionals may alleviate some negative stress before anxiety, depression, and other mental health disorders develop, or allay symptoms of these disorders when they already exist.
Academic Persistence

Like student mental health, attrition is a serious concern in higher education. Only 59% of students complete their college education in six years or less (U.S. Department of Education, 2017c). The statistics are even worse for first-generation students. In a nationwide study of over 2000 students starting 4-year colleges in 2011-12, 31.9% of students for whom neither parent had education beyond the high school level had left college by Spring 2014, compared to 12.1% of their peers (U.S. Department of Education, 2017d). A study of the ten-year outcomes of nearly 15,000 students who were high school sophomores in 2002 found that, by 2012, 20% of first-generation students had earned bachelor’s degrees, compared to 40% of students for whom at least one parent completed college (Redford, Hoyer, & Ralph, 2017).

Most of the students in the current study sample worked at jobs outside of school to help support their education, and many also cared for dependents. Combined non-academic work and care obligations of first-generation students in this study added up to almost two hours a day more than their peers’ obligations. Theoretically, better time management may help students to balance employment and family demands with studies, increasing grades and college wellbeing and thus allowing them to remain in school.

Reduced college completion rates are also correlated with race. A national study of millions of students who started college in fall 2016 found college students of color to have different retention (staying at the same college) and persistence (staying in any college) rates than their peers (National Student Clearinghouse Research Center, 2018). Asian students’ persistence into the fall of 2017 was highest, at 85.3%, much higher than the rate for white students, which was 78.6%. Black and Hispanic students’ persistence
rates were markedly lower: a year after they started, only 67.0% of black students, and 70.7% of Hispanic students, were still in college.

Four- and six-year college completion rates are particularly alarming for black students. Of a large cohort of students starting college in 2011, only 21.5% finished their degrees in four years (U.S. Department of Education, 2017). This figure has held relatively steady in cohorts with starting dates back to 1996, while the four-year graduation rates for other races and ethnicities showed a linear rise. Between the 1996 and 2011 cohorts, whites’ four-year graduation rate rose from 36.3 to 46.3%, and Hispanic students’ rate rose from 22.8 to 32.5%. Similar disparities were seen in six-year graduation rates. While the number of students dropping courses in the current study (six) was too low to support any strong conclusions, it was remarkable that, of the five non-completers for whom race was reported, three were Black, one was Hispanic, and only one was White. In the study sample overall, 57.8% were White, 11.9% Hispanic, and 5.5% Black.

National persistence rates are also low for older college students: only 52.6% of students starting college when they were 24 or older in 2016 were still in college the following fall (National Student Clearinghouse Research Center, 2018). This is significant for the current study, since many participants were age 33 or older.

Not surprisingly, persistence rates were higher at four-year colleges, and lower at two-year institutions. The institution participating in this study has an overall graduation rate of 84%; breakdown by first-gen status and race/ethnicity was not available.

Mental wellbeing also plays an important role in college persistence. The global percentage of students who had left college reporting mental health problems in the past
12 months was even higher (nearly one in three) than the one-in-five global rate for students who finished their degrees (Auerbach et al., 2016).

Technology

Another way that postsecondary education is changing is the mode of delivery. The amount of course content that appears on-line has skyrocketed: between the fall of 2002 and the fall of 2011, the percentage of U.S. higher education students enrolled online rose from 9.6% to 32.0% (Allen & Seaman, 2013). By 2012, only 13.4% of U.S. higher institutions had no on-line course offerings (Allen & Seaman). Even for brick-and-mortar classes, the use of on-line learning management systems (LMS’s) is now widespread. A recent nationwide survey of over 400 U.S. colleges and universities found 90% used a campus-wide LMS such as Moodle, Canvas or BlackBoard (Campus Computing Project, 2015).

The biggest change may be the amount of time that students spend on the Internet. Students can use their phones or smart watches to tell the time, so they no longer need analog wristwatches. Inability to disconnect from social media, news, games, email, shopping, and even irrelevant academic research is nearly universal among the college and graduate students this author strategizes with on time management. Most of them get alerts of new messages on their cell phones, too, and this can be distracting during study time.

Studies of higher education time management conducted 10 or more years ago may not generalize well to today’s students. In a time when few college students use pen and pencil, a question like “do you carry an appointment book” (from the Time Management Behavior Scale (TMBS), Macan, 1994) is out of place. Commonly used
time management studies do not ask about use of electronic devices, either as aids to time management, or as distractions. For the current study, two items in the TMBS were adjusted for currency: “appointment book” was replaced with “planner or online calendar” on one item, and “or my phone” was added after “notebook” on another.

Researchers are searching for interventions for Internet addiction (Khazaei, Khazaei & Ghanbari-H, 2017). Even when Internet use does not rise to the level of addiction, though, it can still detract from academic achievement and other goals. In a 2010-2011 study of 458 college students at a large U.S. university, students reported spending an average of just under four hours and 15 minutes per day online, and spending an average of two hours and 45 minutes using social media or watching TV, movies or videos (Panek, 2014). These hours did not include smart phone use, or any emailing or texting. Online video use was negatively associated with study time, and there was a trend in this direction for the other studied media. Therefore, the current study included a question on non-work screen time, and another on multitasking.

Learning Analytics

Until recently, most studies of time management and other factors in student success relied on self-report surveys. Now that course and student data have moved online, researchers are starting to use this data to explore and predict student behavior. Learning analytics can use LMS logs for objective reports on the timing, duration, and regularity of access to course materials, among many other variables. There has been little research that combines the self-report and demographic learner data with LMS data, though; this study was designed to help remedy that.
Research Review

There is extensive research on time management in postsecondary students, both using self-report measures, and using log data from course management platforms. Learning analytics studies tend to use aggregated data, however, and there is little research combining self-report and demographic data with log data. Not much is known about whether self-report or log data better predicts student success.

Defining and Measuring Time Management with Self-Report Data

Time management is an important component of self-regulation and self-regulated learning (Wolters, Won, & Hussain, 2017; Sitzmann & Ely, 2011 (focused on planning); Terry & Doolittle, 2008). It is commonly described as goal-oriented and behaviorally based (Claessens, van Eerde, Rutte, & Roe, 2007). It can include executive functions like prioritizing, planning, organizing, monitoring, getting started, and sticking to tasks; basic skills like keeping a balanced life and not saying “yes” to too many things; and strategies for efficient use of time. The term may refer to behaviors, knowledge of skills, attitudes, perceptions, or dispositions.

Macan’s Model of Time Management. Probably the most widely cited effort to create a valid time management measure and break time management into multiple dimensions has been that of Therèse Macan (e.g., Macan, Shahani, Dipboye, & Phillips, 1990; Macan, 1994). Macan’s model of time management had four dimensions: Goals, Mechanics, Preference for Disorganization (reverse scored), and Perceived Control of Time. Macan (1994) used path analysis to place Perceived Control of Time between the first three dimensions and outcomes of time management, such as stress.

Macan’s four dimensions of time management correspond well to other models.
For example, Hellsten (2012) reviewed the literature and listed seven behaviors most commonly associated with time management: Analyzing Time, Prioritizing, Goal Setting, Planning, Scheduling, Organizing, and Creating Good Habits. Claessens et al. (2007) reviewed empirical studies from 1982 to 2004 and listed three activities most commonly associated with time management: Assessment of Time & Awareness of One’s Capabilities, Planning, and Monitoring. Britton and Tesser (1991) developed an 18-item Time Management Questionnaire for U.S. college students with three subscales: Time Attitudes, Short-Range Planning, and Long-Range Planning. Trueman and Hartley (1996) tested a slightly shorter, 14-item version on British postsecondary students and found it to have two dimensions: Daily Planning and Confidence in Long-term Planning. Another multidimensional approach is that of Kearns and Gardiner (2007). They surveyed university staff and students and named four dimensions in time management: Having a Clear Career Purpose; Planning and Prioritizing; Avoiding Interruptions and Distractions; and Being Organized. Feather and Bond (1988) explored “time structure, defined by the degree to which individuals perceive their use of time to be structured and purposive” (p. 321, emphasis in original). Their 26-item Time Structure Questionnaire (TSQ) asked some questions that were similar to those by researchers reported above, such as “Do you plan your activities from day to day,” which is similar to Britton & Tesser’s 1991 “I make a list of things to do each day”, and “Do you ever feel that time just seems to slip away,” which is similar to Macan’s question on perceived control of time. However, many of the questions related to slightly different constructs, like self-efficacy (“Do you give up easily once you’ve started something?”) or past/present/future time orientation. The TSQ measure factored into five dimensions: Sense of Purpose,
Structured Routine, Present Orientation, Effective Organization, and Persistence.

Table 1 summarizes all of these dimensions. As shown, most can fit roughly into one or more of Macan’s categories.

Table 1

*Hypothetical Correspondence Between Dimensions of Time Management*

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<thead>
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<tbody>
<tr>
<td><strong>Goal Setting/ Prioritizing</strong></td>
<td>Sense of Purpose</td>
<td>Long-Range Planning</td>
<td>Planning and Prioritizing (K&amp;G)</td>
<td>Prioritizing</td>
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<tr>
<td></td>
<td></td>
<td></td>
<td>Having a Clear Purpose (K&amp;G)</td>
<td>Goal Setting</td>
</tr>
<tr>
<td><strong>Mechanics</strong></td>
<td>Structured Routine</td>
<td>Daily Planning (T&amp;H)</td>
<td>Planning</td>
<td>Planning</td>
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<td></td>
<td></td>
<td>Short-Range Planning</td>
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<td>Scheduling</td>
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<td></td>
<td>Long-Range Planning</td>
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<tr>
<td><strong>Preference for Disorganization (Reverse Scored)</strong></td>
<td>Effective Organization</td>
<td>Being Organized (K&amp;G)</td>
<td>Organizing</td>
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<tr>
<td><strong>Perceived Control of Time</strong></td>
<td>Persistence</td>
<td>Time Attitudes</td>
<td>Awareness of Capabilities</td>
<td>Analyzing Time</td>
</tr>
<tr>
<td></td>
<td>Present Orientation</td>
<td>Confidence in Long-Term Planning (T&amp;H)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
**Time Management Behavior Scale (TMBS).** Macan’s four dimensions developed out of the TMBS, a self-report survey created by Macan and colleagues (1990). The researchers gave the original TMBS to 288 students at a large U.S. state university. Students were mainly at the college level, but some had advanced further, and many had jobs outside of school. The average age was over 24, and the range went to 44. Of students reporting demographic information, 73.9% were White, 12.7% Asian, 7.6% Black, and 5.7% Hispanic. Survey results overall correlated in the expected directions with “role ambiguity, somatic tension, job and life satisfaction, self-rated performance, and GPA” (Macan et al., p. 764). Factor analysis of the scale revealed four dimensions: Goal Setting and Prioritizing, Mechanics (including planning and scheduling), Perceived Control of Time, and Preference for Disorganization.

In a follow-up study, Macan (1994) reasoned that Perceived Control of Time would mediate the other three factors, since perception of control reduces stress, not behavior. Path analysis confirmed her hypothesis. The study also showed good convergence between third-party and self-report versions of the TMBS. The TMBS has good internal and external validity as a measure of the time management behaviors described in the popular literature (Adams & Jex, 1997; Macan, 1994).

**Student Satisfaction with Time Scale (SSTS).** The SSTS came out of a study this author conducted with faculty sponsor Shelley Carson, and with a grant from Harvard’s Graduate Student Learning Support program (Bisbee, 2016; Bisbee & Carson, 2017). The study compared the effectiveness of participating in a four-week time management workshop versus receiving handouts alone.
Between 2014 and 2016, over 100 graduate students studying public health and design at a top-tier university in New England took pre- and post-intervention surveys with the SSTS and other measures. Students in the experimental group participated in the workshops and received weekly handouts summarizing the material discussed, while active controls only received the weekly handouts. The workshops covered four topics: Prioritizing and Planning, Optimizing, Time-Outs, and Scheduling.

The inventory had two parts: Being/Balance, measured by 14 items asking how satisfied the student had been over the past four weeks with ability to devote quality time to various life domains; and Doing/Skill, measured by 13 items asking similar questions about the student’s satisfaction with their ability to use time well. While the strategies covered in the workshops spanned all four of Macan’s dimensions of time management, the survey items appeared to corresponded most closely to Perceived Control of Time, due to the “how satisfied have you been with” prompt.

Higher scores on the SSTS reflect greater post-intervention satisfaction with quality time allotment and application of time management skills. The questions about satisfaction with one’s ability to manage time (Doing/Skill or SSTS-Do) are included in the current study survey; the text is in Appendix C.

107 participants (31 workshop and 76 active control) at the two schools provided valid pre/post change scores. Analysis of these scores showed significantly greater improvement in both Being/Balance ($F_{1,105} = 8.63, p = .004$) and Doing/Skill ($F_{1,105} = 20.05, p < .001$) for workshop participants than active controls who only received the workshop handouts.
87 study participants (24 workshop and 63 active control) also took follow-up surveys anywhere from one to nine months after the post-intervention survey. Analysis again showed significantly better results for the workshop participants, as shown in Appendix D. While this was a preliminary study, with limited random assignment and varied survey administration schedules, the results indicated more research was worthwhile.

Identifying Patterns of Actual Time Use with Learning Analytics

Most postsecondary courses today that are online use LMS’s to provide student access to syllabi and course materials, complete and submit assignments, take tests, engage in discussions, receive grades, and other functions. A Fall 2017 survey of all accredited U.S. colleges and universities with 500 or more students (over 3,500 schools) found only 6.6% did not use an LMS (Edutechnica 2017). The most common LMS’s in use today are Canvas, Blackboard, and Moodle (Edutechnica, 2018).

In the past, researchers had to use time logs and other self-report measures to get data on actual use of time. With course platforms like Canvas, Moodle and Blackboard, accurate evidence of every time a student has clicked on the course web sites can be converted into variables representing timing, duration, intensity, and regularity of study. Students may remain logged in, sometimes for days, when they are not working, and clicks do not confirm whether students are focused on their course work, so the data is not precise. Still, overall patterns in time use, whether by month, day, hour, or second can be explored in ways they could not a decade or two ago. As organizational behavior researchers Shipp and Cole (2015) have asserted, “[t]iming issues such as patterns, duration, cycles, and time lags need to be studied more frequently in almost all areas of
Learning analytics was defined during the 1st International Conference of Learning Analytics of 2011 as “the measurement, collection, analysis, and reporting of data about learners and their contexts, for the purposes of understanding and optimizing learning and the environments in which it occurs.” (Siemens, 2013, p. 1382). There is significant overlap between learning analytics and educational data mining, and the two are closely related. In a much-cited article on educational data mining, Romero & Ventura (2013) distinguish the two. One difference they assert is that educational data mining focuses on automated discovery of patterns to optimize education, while learning analytics is more focused on human interpretation and judgment (Romero & Ventura, 2013). Scholarship in the field has grown quickly: a 2018 literature review identified 689 peer-reviewed articles on learning analytics published since the year 2000 (Sønderlund, Hughes & Smith, 2018). 577 of these articles related to using learning analytics for prediction, and 41 related to using learning analytics to evaluate interventions.

To date, most learning analytics studies have focused on LMS data alone, with no learner-specific data (Conijn et al., 2017). Learning analytics studies have also largely ignored theory (Conijn et al., 2017; Ellis, Han & Pardo, 2017). Ellis, Han and Pardo found that results were far more predictive when the research was theory-based and included self-report data. The current study includes self-report data linked to LMS data, and aims to be well grounded in the existing time management literature.

Predicting Grades, Wellbeing, and Course Persistence

Whether time management measures are being used to identify at-risk students, or to identify behaviors associated with success, predictive value is critical. This study used
three measures of success: grades, wellbeing, and course persistence. Current evidence on the predictive value of each is reviewed below.

**Grades.** A 2007 literature review reported mixed results for time management’s correlation with grades (Claessens, van Erde, Rutte, & Rowe, 2007). Based on a more recent review, researchers stated: “Although the studies in this area support a tentative connection between college students’ time management and their academic functioning and performance, it is far from conclusive” (Wolters, Won, & Hussain, 2017, p. 383).

Using self-report surveys, many researchers have identified positive correlations between time management and grades (e.g., Britton & Tesser, 1991; George, Dixon, Stansal, Gelb & Pheri, 2008; Landrum, Turrisi & Brandel, 2006, Macan et al., 1990; MacCann et al., 2012; Onuka, 2012; and Trueman & Hartley, 1996). Others have found less support for the association (Richardson, Abraham & Bond, 2012). Given the variety of measures used to assess time management and academic success, and the variety of populations studied, it is not surprising that results have varied as well.

The authors of a 2005 report finding study time was not predictive of GPA asserted in their introduction: “researchers have consistently found a weak or unreliable relationship between the weekly amount of reported study time and grade point average (GPA) for college students” (Plant, Ericsson, Hill & Asberg, 2005, citing several studies). Claessens et al. (2007), and Nonis and Hudson (2005) reviewed the literature and found some studies confirming positive correlations, some finding none, and even some finding negative correlations between time management and academic performance. A 2012 meta-analysis found only a weak or nonexistent correlation between time spent studying and GPA (Richardson et al., 2012).
There has been little research on how time management’s ability to predict grades varies by subpopulation in U.S. postsecondary students. This is unfortunate, as relationships between time management and academic achievement may be stronger for some groups, such as part-time learners, than for others. MacCann et al. (2012) surveyed 556 students at 20 U.S. community colleges. 147 of these students were part-time. While the authors found no significant correlation between time management and grades in the sample overall, they found a significant positive correlation for part-time students. The authors hypothesized that, among the part-time students, time management mediated the relationship between the trait of Conscientiousness and GPA.

Time management is part of self-regulated learning, and at least one study of university students found no significant correlation between self-regulated learning and grades (Bruso & Stefaniak, 2016). Another study of U.S. college students used self-report and time logs to measure study time (Plant, Ericsson, Hill & Asberg, 2005). They then regressed a number of factors on fall GPA: prior GPA, standardized test scores, and study environment, attendance, planning, hours of work, and hours of partying. Study environment, rather than study time, was the only factor that had a direct relationship with fall GPA without accounting for prior GPA. Students who studied alone without distractions got better grades (Plant et al., 2005).

The most commonly cited support for a correlation between time management and grades is Britton and Tesser’s (1991) prospective study of 90 introductory psychology college students. Participants completed a self-report survey on time management in 1983. Four years later, the students took the survey again. Britton and Tesser identified three factors from the results: Short-Range Planning, Time Attitudes,
and Long-Range Planning. The researchers found that Short-Range Planning and Time Attitudes predicted more of the variance in participants’ grades than their SAT scores. The correlation between Short-Range Planning and GPA ($r = .25$) was small to moderate, while the correlation between Time Attitudes and GPA ($r = .39$) was moderate. Long-Range Planning had no significant correlation with GPA (interestingly, it did have some ($r = .29$) correlation with SAT scores). Other studies have also found correlations between time management and grades in postsecondary students (Burlison, Murphy & Dwyer, 2009; Macan et al., 1990, Thibodeaux, Deutsch, Kitsantas & Winsler, 2017).

When it comes to procrastination, Steel (2007) ran a meta-analysis and found a negative correlation between procrastination and grades. Most studies using objective indica of procrastination have shown a negative association (Kim & Seo, 2015; see also Balkis, 2013). Studies of self-reported procrastination may not report actual procrastination accurately, however. The most commonly used self-report measure for procrastination is Solomon and Rothblum’s 1988 Procrastination Assessment Scale – Students or PASS (Kim & Seo). Kim and Seo performed a meta-analysis and found a large discrepancy between the effect sizes of self-reported procrastination versus externally reported procrastination on academic performance. The PASS showed even less of a relationship between procrastination and academic performance than other, less commonly used and therefore less validated, self-report measures.

While procrastination looks at preferences, pacing style looks at actual effort. This was noted in a study that looked at pacing styles in over 1000 postsecondary and working adults (Gevers, Mohammed & Baytalskaya, 2015). The researchers defined pacing style as “the distribution of effort over time in working toward deadlines” (p. 21).
They used self-report surveys to assess three pacing styles: evenly distributed effort; early and late effort distribution, or U-shape; and deadline pacing style, which resembles procrastination but includes purposeful delay, with no positive or negative connotation. No correlation between grades and any of the three styles emerged.

Like pacing styles, time logs give a more objective measure of time management or procrastination. In one study, researchers asked 231 undergraduates at a Canadian university to keep five-day time diaries listing their activities in 30-minute increments (George, Dixon, Stansal, Gelb, & Pheri, 2008). They ran correlation and regression analyses on the time diary data and found study time, early awakening, and reduced time on passive leisure to be significant predictors of GPA. Only intelligence and responses to a single self-report item on time management were more predictive.

With learning analytics, researchers can now obtain much more objective data, in much larger quantities. Predictors of grades found to date have included, among others, early access to course sites (Conijn et al., 2017; Jo, Kim, & Yoon, 2015); lack of last-minute assignment submission (You, 2015); and lack of cramming, consistency of access, and pacing (Asarta and Schmidt, 2013). Each of these is discussed briefly below.

Learning analytics studies have shown that early initial access to the course website has a significant positive correlation with academic achievement (Conijn et al., 2017; Jo, Kim, & Yoon, 2015). You (2015) used learning analytics to explore the impacts of procrastination on academic achievement in 569 students taking an introductory college level course in Seoul, South Korea. LMS indicators of procrastination were late access to online lectures, and late submission of assignments. These indicators were significant negative predictors of grades in the course.
In a study of 200 employees taking a month long, 12-module online course sponsored by their Korean company, Jo and colleagues (2015) correlated data summaries for course takers’ total login time, frequency of login, and regularity of login throughout the course with grades on a final, 20-item multiple choice test. The researchers found the pattern that most closely correlated with academic achievement was not frequency or length of access, but rather regularity of access: even when a student spent less time overall on the course, with a regular length of time between logins, that student was more likely to do well in the course.

Asarta and Schmidt (2013) studied log records of 179 students in a blended introductory business course. The most important variables they identified were “anti-cramming,” consistency, and pacing. They measured anti-cramming by the number of lectures accessed three or more days before exams, and pacing by number of lectures accessed by the appointed time. For consistency, they gave one point for each between-class interval in which a student accessed a lecture. “Anti-cramming” was most predictive, and consistency and pacing were also highly correlated ($p < .001$) with grades.

You (2015) achieved similar results studying 569 undergraduates in a large online Korean undergraduate course. The researcher used learning management system-identified “absence” (failure to access materials within the requested time frame) and late submission of assignments as measures of procrastination; a regression analysis identified a significant relationship between academic procrastination and academic achievement. Particularly as the semester progressed, absence and late submissions emerged as strong indicators of course grades, accounting for almost a third of final exam score variance.

In a study using Moodle data to predict course grade, researchers found two
variables to be particularly important: early access to course materials, and irregularity of intervals between students’ access to their course site (Conijn, Snijders, Kleingeld, & Matzat, 2017). Jo, Kim & Yoon (2015) also found early initial course site access to be a predictor of academic achievement.

Surprisingly, there were studies of the impact of study times of day on postsecondary students. The only researchers to address it were Zhang, Zhang, Zou, & Huang (2018). These researchers included the variable time of day in an LMS analysis of over 1000 students, likely high school age (the report refers to them as “girls and boys”) in a hybrid course that had 22 different teachers. The researchers divided the day into four six-hour periods, and found that the vast majority of online activity occurred between noon and midnight, nearly 20% occurred between 6 am and 12 pm, and less than 3% of activity occurred between midnight and six a.m. 48 of the 64 students in this early morning category had scores on a comprehensive exam that were higher than the scores of about 75% of students in the course studied. The authors suggested further investigation into the early morning studiers, and this study contributed to that effort.

Wellbeing. When it comes to correlations between time management and non-grade indicators of academic success such as mental health and wellbeing, there is less literature. One exception is Feather & Bond’s 1988 study of self-reported “time structure,” which relates to “structured and purposive” use of time (p. 321). In a study of over 500 Australian students, they found significant correlations between time structure and life purpose, self-esteem, and many aspects of physical and mental health. Misra and McKean (2000) surveyed 249 U.S. college students, using Macan et al.’s (1990) original four-dimension model to measure time management behaviors. They found a strong
negative association between all four dimensions (Setting Goals and Priorities, Mechanics of Time Management, Organization, and Perceived Control of Time) and academic stress. Interestingly, the negative association between leisure time and stress was weaker than the time management one.

Procrastination studies have found negative correlations with academic satisfaction (Balkis, 2013), and stress and illness (Tice & Baumeister, 1997). Balkis surveyed 290 Turkish undergraduates and found a direct relationship between procrastination and both academic life satisfaction and academic performance, and a mediating role for rational beliefs about studying between procrastination and these variables. Tice and Baumeister studied about 100 college students and found that while procrastination early in the semester was associated with reduced stress and illness, over the long term it was associated with increased stress and illness, and lower grades. The authors concluded that was a negative use of time.

A few studies have found a negative relationship in postsecondary students between time management and stress, or a positive relationship between procrastination and stress (e.g., Feather & Bond, 1988; Häfner et al., 2014; Häfner et al., 2015; Misra & McKean, 2000; and Tice & Baumeister, 1997; but see Macan et al., 1990), and a laundry list of other problems like hopelessness, anxiety, depression and anomie (e.g. Feather & Bond). Still, more research is needed. To help fill this gap, the College Student Subjective Wellbeing Questionnaire (CSSWQ, Renshaw, 2016) was administered to measure “college wellbeing” in the current investigation.

Renshaw and Bolognino (2014) developed and validated the original 15-item CSSWQ on a sample of 945 undergraduates, and found it to be a good predictor of
A limitation the researchers noted was that the participants in both the 2014 and 2016 studies were predominately White undergraduates at a southern university. First-generation status was not reported. The authors called for further research with more diverse samples, comparing the CSSWQ to other outcome measures.

Significance of the Study

The research cited above shows no consistent pattern of how time management behavior relates to grades, and little research about how it relates to wellbeing. Also, there is little research connecting the older self-report method of time management study to the new learning analytics one. Most learning analytics research has used aggregated data, making it impossible to connect individual student log data to self-reports. Aside from an interesting study of school children in China, a literature review revealed no learning analytics studies examining the relationship between study times of day and success. Finally, there was little information on how demographics like first-generation status may mediate time management’s impact on academic success. This study should help fill some of these gaps.

The current study improved on past research methods by using updated survey
Instruments, objective as well as subjective measures of time management, and college wellbeing as one dimension of academic success. Self-report measures used 20 questions representing Macan’s dimensions of Goal Setting and Prioritizing, Mechanics, and Perceived Control of Time, as adapted by Lay and Schouwenberg (1993) with a few questions from Britton & Tesser (1991). Also included were 13 newly developed self-report items based on common issues reported by students, and a question on hours of sleep. The follow-up survey contained self-report questions on multitasking, time spent working for pay or caring for dependents, and time spent online not working or studying. The follow-up survey also asked students which of 11 time management tools they used, and offered open response for any other tools. Study times of day were extracted from Canvas data.

It was expected that this research would identify key factors in time management, and shed light on how time management attitudes, skills and behaviors correlate with grades, course persistence and college wellbeing. Findings may help improve academic support for today’s diverse, electronically connected student populations.

Study Purpose and Research Questions

Primary goals of the current investigation were determining the importance of time management to student success, pinpointing the aspects of time management that are most important, and assessing the utility of self-report versus objective learning analytics measures. The four questions addressed, in students in a continuing education program at a large northeastern U.S. university, were:
1. Does time management account for a significant amount of the variance in grades, college wellbeing, and course completion?

2. Which time management factors are the best predictors?

3. Which variable types are better indicators: self-report measures, or variables drawn from course log data?

4. Do these patterns vary for first-generation college students?
Chapter II

Method and Materials

This study used online course participation logs and self-report data from 10 courses in a large continuing education school at a northeastern U.S. university. Most self-report data were collected from an online survey in the fall. Final grades and information about students’ time allocation and management tools were included in a shorter follow-up survey in January. Behavioral data were collected throughout the semester from Canvas, the school’s online course management system (LMS).

Participants

One hundred and nine students (73.4% female; none identified as other than female or male) joined the study by taking an online survey after the first month of the fall semester. Eleven percent of the students were ages 18-22, 19.3% were between ages 23 and 27, 19.3% were between ages 28 and 32, and 50.5% were aged 33 and older. The breakdown for self-reported race/ethnicity/national origin (n=103, as 6 participants did not disclose race) was 58.7% White, 14.7% Asian, 11.9% Hispanic, 5.5% Black, and 3.6% Biracial or Other.

The university’s Institutional Review Board approved the study proposal, and students gave informed consent each time they took a survey. A separate research unit of the university de-identified all survey and Canvas data before sending the research. Initially, instructors of 32 courses were contacted. Ten of them distributed an invitation
to join the study to their students. Based on publicly available data, 1133 students had registered for these courses by the start of the semester. One hundred twenty-three of these students emailed about participating. These emails were answered with informed consent information and a link to the first survey. In the email, participants were reminded that their instructors and the researchers would not be able to connect the survey or Canvas data to their individual identities, so their responses could not affect their grades. The only exception was an abnormal psychology course in which students were already required to participate in a study for course credit. Five of the study participants opted to participate in the study for credit. These students told their instructor they had participated, but they knew she could not connect their study data to their grades. The end of the survey offered a link where students could anonymously enter their emails if they wanted to participate in a raffle to win one of two $50 Amazon gift cards.

To increase numbers and ensure that procrastinators were included in the study, the deadline for the fall survey was extended twice. As needed, up to three reminders were sent. Ultimately, 109 students completed valid surveys. This would have been 110, but one student was unable to make the survey function on his computer work.

The January survey was emailed to everyone who had completed the fall survey. As an incentive to increase the response rate, participants were informed that if 75 of them completed surveys within three days, a third $50 Amazon gift card would be added to the raffle. After individual emails and reminders, nearly 80% completed the follow-up survey in the four days it was open. Figure 1 shows participant flow.
123 students emailed researcher
10.1% response rate of eligible students

Instructors of 10 courses contacted 1133 eligible students
31.3% course participation rate

32 course candidates identified

IRB approval received

109 valid survey responses received, fall 2018
88.6% participation rate
(9.6% of original eligible students)

Follow-up survey link emailed to 109 participants

87 valid survey responses received, January 2019
80.0% participation rate (7.7% of original eligible students)

Figure 1. Participant Flow
One-way ANOVA showed a significant difference in race/ethnicity between the one- and two-survey takers ($F_{2, 85} = 11.42, p = .001$). The biggest difference was between proportions of Black and White students: 42.9% of the students who did not complete the second survey identified as White or Caucasian, and 23.8% identified as Black or African American. For students taking both surveys, 63.2% identified as White. Only one of the six students in the study who identified as Black, or 1.1% of participants, took the second survey. There were no significant differences between one- and two-survey takers in first-generation status, age, gender, course background, course load, or most recent GPA.

Financial Accounting and Web Design, representing 14.9% of the participants who took both surveys, were fully online courses. The other courses allowed online or in-person attendance. On the fall survey, 84.4% of students said they expected to take their courses fully online. In January, less than a third (31.0%) said they had never attended a lecture or class in person. Given the original intent of so many students to attend fully online, it is likely that many of the 69% reporting they had attended at least one class in person still attended most on-line. Even if they did attend lectures in person, students had to go online for readings, quizzes, discussions and other assignments.

Through the 10 study courses, the 109 participants who completed the survey in the fall represented four subject areas: math and statistics (56.0%), social sciences (37.6%), physics (4.6%) and computer science (1.8%). Ratios were still relatively similar, but more evenly distributed, at follow-up. Details about the ten courses participating in the study are in Appendix B.
Measures

The fall survey requested the following demographic questions: sex/gender; age; race/ethnicity/national origin; whether parents or guardians attended college; whether the student was seeking a degree or not; number of courses taken; intended mode of attendance in lectures (in-person, streaming live online, or on-demand online); past GPA; and level of prior knowledge in the course. Students had a “prefer not to answer” option for any potentially sensitive questions, including those on gender identity, race/ethnicity, first-generation status, degree status, course information and GPA. The January survey also asked how many weekly hours the student had worked at a paying job, cared for a dependent, or spent online for leisure during the fall semester. Both surveys requested students’ time zones (Canvas reports use Coordinated Universal Time).

Outcome measures were final grade, course completion, and college wellbeing. Participants reported their final grades and course completion status on the follow-up survey. For students who did not complete the follow-up survey, course completion was inferred from Canvas course site activity. College well-being was assessed through a survey measure described below. Predictors were three self-report survey instruments, also described below; factors derived from these instruments; several single-item questions; and times of day from Canvas log data.

Survey Instruments

Students took the first survey about one month into the fall semester. This time was targeted to ensure significant experience in the course, while avoiding the anxiety surge that comes with mid-term exams.
Multiple-item measures. The fall survey included three self-report instruments with 49 questions. Two instruments assessed time management: the Time Management Behavior Scale (TMBS, Macan et al., 1990, as adapted, with a question added from Britton & Tesser, 1991, by Lay & Schouwenberg, 1993), and the Doing/Skill subscale of the Student Time Satisfaction Scale (SSTS-Do, Bisbee, 2016).

Peer-reviewed journals have reported reliability and validity testing for both the TMBS (Adams & Jex, 1997; Macan, 1994), and the CSSWQ (Renshaw, 2016). The TMBS has had varying numbers of items, depending on the administration, and has used a five-point response scale. The CSSWQ has 16 items, and uses a seven-point response scale. For ease of administration in the current study, a five-point scale, from “strongly disagree” to “strongly agree,” was used for both measures. Participants were prompted to select the answer that best described them as they had been during the semester the survey was taken.

The SSTS-Do (Bisbee, 2016) is a new measure; results of reliability testing for the current study were good ($\alpha_c = .92$). It is administered on a five-point scale, and applies to the semester the survey is taken. Participants are prompted to report how satisfied they have been with their ability to do things like get started on big tasks, plan ahead, and get places early or on time.

The history of all three measures is discussed in the Review chapter of this thesis. Table 2 summarizes the survey measures, along with reliability alphas. Full text of measures is in Appendix C.

Single-item measures. In addition to demographic items, the fall survey included a question about how many hours of sleep each student got on average. A follow-up
survey was distributed in January. The follow-up survey asked students whether they had completed the study course, and if so, what their grades were. The survey also asked which time zone the student been in for most or all of the semester, and whether or not they attended any lectures in person. The survey asked how frequently the student multitasked, and the amount of time the student spent online when not working for a course or job. Finally, there was a laundry list question about what tools students used for time management.

Canvas data. The courses participating in the study used the Canvas LMS as a platform for their course materials, lectures and tests. All of the courses were designed so that students could take them fully online; two were fully online. For each study participant, log data from the participating course’s Canvas website was extracted for from the start of the semester up through exams. This data included each time a student clicked on any part of the site, organized by date and time. A third party in a research unit of the university downloaded Canvas data for each participant, and created an anonymous key connecting each participant’s survey data with their Canvas data. Canvas uses Coordinated Universal Time, so each participant’s timestamps were converted to their own time zone, accounting for daylight savings as needed. Appendix E details the processing of this data. Final variables from the Canvas data were study times of day, based on frequency of clicks, by percentage, in the following time of day segments: 12 am to 6 am, 6 am to 12 pm, 12 pm to 6 pm, 6 pm to midnight, 1 am to 4 am, and 5 am to 9 am.

Data Analysis

As detailed in Appendix E, 116 fall surveys were returned, and 109 were valid.
Internal reliability for the TMBS, SSTS, and CSSWQ, was assessed. Deleting several variables that did not contribute to the scales’ reliability or scope left 49 self-report items. All final scales and sub-scales had Chronbach’s alpha > .7, and are listed in Table 2.

Table 2

*Survey Measures With Chronbach’s alpha*

<table>
<thead>
<tr>
<th>Name</th>
<th>Subscale</th>
<th>Items</th>
<th>Old α</th>
<th>New α</th>
</tr>
</thead>
<tbody>
<tr>
<td>TMBS – Time Management Behavior Scale</td>
<td></td>
<td></td>
<td></td>
<td>.84</td>
</tr>
<tr>
<td></td>
<td>Mechanics</td>
<td>6</td>
<td>.79</td>
<td>.72</td>
</tr>
<tr>
<td></td>
<td>Setting Goals and Priorities</td>
<td>7</td>
<td>.76</td>
<td>.81</td>
</tr>
<tr>
<td></td>
<td>Perceived Control of Time</td>
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<td>.73</td>
<td>.75</td>
</tr>
<tr>
<td>SSTS – Student Satisfaction with Time</td>
<td>Skills/Do: Ability to Manage Time</td>
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<td>N/A</td>
<td>.92</td>
</tr>
<tr>
<td>CSSWQ – College Student Subjective</td>
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<td>4</td>
<td>.86</td>
<td>.82</td>
</tr>
<tr>
<td>Wellness Questionnaire</td>
<td>College Gratitude</td>
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<tr>
<td></td>
<td>School Connectedness</td>
<td>4</td>
<td>.83</td>
<td>.73</td>
</tr>
<tr>
<td></td>
<td>Academic Satisfaction</td>
<td>4</td>
<td>.88</td>
<td>.75</td>
</tr>
</tbody>
</table>

a. Macan et al. (1990); one question from Britton & Tesser (1991). Adapted for this study from the version by Lay & Schouwenburg (1993), with slight wording changes (e.g. “or use my phone” added after “notebook”; “or online calendar” added after “planner”).
b. Bisbee (2016)
c. Renshaw & Boligno (2104); Renshaw (2016). There are slight wording changes.
Factor Analysis

Factor analysis was conducted on the self-report time management measures to test the TMBS against the SSTS, and to reduce possibility of Type II error. Based on Cohen’s (1992) suggestions for detecting varying effect sizes at Power = .80 and alpha = .05, there was little power to detect small effects in multiple regression in a sample of 109. A sample size of 481 would have been needed, even with only two predictors, for adequate power. To detect a medium effect in two predictors, though, Cohen suggests a sample size of 67; this number rises to 107 for eight predictors. Most of the current study n’s were between 79 and 109. If there were four factors, as Macan had found, the sample size seemed adequate.

To begin, a Principal Components Analysis was conducted on the fall survey TMBS and SSTS results with orthogonal (Varimax) rotation. To further account for the small sample size, an eigenvalues of .5 or more was required. The number of components was not predetermined. To ensure that the components analysis was equivalent to a pure factor analysis, it was also run in Principal Axis Factoring with oblique (Direct Oblimin) rotation, and with Maximum Likelihood Estimation. Results were the same, and PCA with Varimax was used for the rest of the analyses.

Grade and College Well-Being: Linear Regression

Multiple linear regression was used to assess the relationship between predictors and the continuous outcome variables, grades and college well-being. Initial forced-entry hierarchical regression did not yield a good model. To broaden the search for predictors, separate regressions were run stepwise. Stepwise regression has generally been frowned upon for exceeding acceptable case to variable ratios, and potentially finding meaningless
correlations (Babyak, 2004). Since this was an exploratory study, and also since the low sample size made false positives unlikely, it was decided that the benefits of making good use of the data outweighed the drawbacks of stepwise regression. As Babyak (p. 420) has said, it is important to make the best use of data exploration, while also understanding the methods and giving results appropriately cautious interpretations.
Chapter III

Results

Three variables were significant predictors of academic success: Satisfaction with Time Use; the TMBS Mechanics subscale; and number of time management tools used. The three indicators of academic success were final course grade, college wellbeing, and course completion. The discussion below describes the study variables, along with the results of the factor analysis used to obtain the Satisfaction with Time Use variable. Overall findings are presented next, after which group differences and other results that indicate possible areas for future research are presented.

Outcome Variables

The lack of variance in two of the three outcome variables presented a challenge for this study. Combining grades and course outcome mitigated this issue.

Grades

As shown in Figure 2, most students reporting their final grades got A’s (61.3%), and the second most common grade was an A- (17.5%). Only a handful got the lowest grades reported, which were C+ (1 student, 1.3%), and C (4 students, 5%). Similarly, only six students failed to complete the course, while at least 93.3% followed through, (log data was unavailable for six students). This lack of variability in grades and course persistence limited the study findings.
Course Persistence

Persistence had even less variance than final grades: based on Canvas log data, only six of 109 students did not complete their courses, and only one of those students took the follow-up survey.

Composite: grade and course completion. Due to the low variance in grades and course persistence, a composite variable of grade with a score of 1.7/C- for students who had not completed the course was created. The best model ($R^2 = .158$, adj. $R^2 = .137$, $F_{1, 79} = 7.332$, $p = .001$) had two predictors: number of time management tools the student reported using to manage time was a negative predictor ($n = 87$, $B = -.113$, $SE = .041$, $\beta =$
-.283, t = -2.722, p = .008), and score on the Mechanics dimension of the TMBS was a positive predictor ($B = 3.16, SE = .111, \beta = .297, t = 2.850, p = .006$). The model for first-gen students was different: number of time management tools was still a negative predictor ($n = 32, B = -1.148, SE = .062, CI [-.276, -.021], \beta = -.386, t = -2.389, p = .024$), but Factor 1, Satisfaction with Time Use, replaced Mechanics as the strongest positive predictor ($n = 31, B = .348, SE = .138, CI [.065, .631], \beta = .456, t = 2.181, p = .018$). The model accounted for nearly a third of the variance ($R^2 = .321$, adj. $R^2 = .269$, $F_{1,26} = 6.149, p = .007$).

The CSSWQ provided adequate variance in results to permit stronger findings. Means and standard deviations for the three outcome variables are in Table 3.

Table 3

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>SD</th>
<th>n</th>
</tr>
</thead>
<tbody>
<tr>
<td>Grade (4.0 = highest, A)</td>
<td>3.68</td>
<td>0.55</td>
<td>80</td>
</tr>
<tr>
<td>Course Completed (1 = yes, 0 = no)</td>
<td>0.94</td>
<td>0.23</td>
<td>103</td>
</tr>
<tr>
<td>Average CSSWQ Score</td>
<td>4.15</td>
<td>0.46</td>
<td>109</td>
</tr>
</tbody>
</table>

Factor Analysis

As detailed in Appendix E and shown in Table E1, exploratory and confirmatory factor analysis of the self-report time management survey items yielded a three-factor model with 15 items. The first factor was Satisfaction with Time Use; it accounted for
28.9% of the variance. It is similar to Macan’s Perceived Control of Time, in that it relates to the students’ subjective sense of whether they are managing their time well. Factor 2, Track and Evaluate, is composed of items from Macan’s Mechanics dimension, and accounted for 18.0% of the variance. Factor 3, Set Intentions, is composed of items from Macan’s Goals dimension, and accounted for 13.9% of the variance.

Predictors
Predictor variables are discussed in Chapter 1 (self-report inventories), and Chapter 2 (single-item responses, Canvas data). Means and standard deviations are summarized in Table 4, followed by a brief summary of significant results. Further discussion is included below for two variables: grades, and study times of day.

Overall Findings
Two of the outcome variables, grades and course completion, had minimal variance. The third outcome variable, college wellbeing, yielded useful results. All predictors listed in Table 4 were assessed for association with outcome variables with t-tests or binary correlations. Most did not achieve significance at alpha = .05 after accounting for family-wise error and controlling for potential confounds.

In regression analysis, Satisfaction with Time Use was a significant predictor of college wellbeing. For a combined grade/course completion variable, number of time management tools used was a negative predictor, and the Mechanics subscale of the TMBS was a positive predictor. Other interesting results for the composite grade/course completion outcome variable were study times of day, and group differences. Important findings are detailed below.
Modeling the three new factors on total CSSWQ with hierarchical forced-entry regression yielded a model with Factor 1, Satisfaction with Time Management, accounting for most of the variance ($R^2$ change = .201, $B = .210$, 95% CI [.092, .328], $SE = .059$, $\beta = .349$, $t = 3.53$, $p = .001$) and Factor 3, Set Intentions, making a small improvement ($R^2$ change = .028, $B = .117$, 95% CI [-.001, .235], $SE = .060$, $\beta = .194$, $t = $)
The model accounted for 23% of the variance in GPA ($R^2 = .229$, adj. $R^2 = .214$, $F_{2,106} = 15.71, p < .001$). Factor 2, Monitoring and Evaluating, did not approach significance. When the same factors were regressed on a composite of final grade and course outcome, none made a significant contribution. The highest $t$ value, for Factor 1, was 1.73 ($p = .088$).

When demographic factors (age, gender, race, first-gen status, course background, whether or not enrolled in a degree program, past GPA, and number of courses) were entered first, the three time management factors no longer made significant contributions to the variance in GPA or college wellbeing. The strongest demographic predictor was prior GPA ($t = 4.397, p < .001$), while none of the other demographic variables approached any significant contribution. The model with past GPA as predictor accounted for a bit more of the variance than the model with Factor 1, Satisfaction with Time Use, had ($R^2 = .264$, adj. $R^2 = .250$, $F_{1,54} = 19.34$, $p < .001$). A model with the course taken variable entered first also negated any impact of the three factors, though it accounted for much less of the variance than prior GPA ($R^2 = .052$, adj. $R^2 = .040$, $F_{1,84} = 4.57$, $p = .035$).

After stepwise regressions, forced entry hierarchical regressions were run using the most promising variables on Final Grade, a final grade/course completion composite, and College Wellbeing. A binary logistic regression was run on Outcome. Results are described below.

**College Wellbeing.** The best model regression yielded for college wellbeing had one predictor, Satisfaction with Time Use. The model accounted for about 20% of the variance; results are detailed in Table 5.
Table 5

*Best Regression Model for Predictors of College Wellbeing (n = 87)*

<table>
<thead>
<tr>
<th>Step and predictor variable</th>
<th>B</th>
<th>SE B</th>
<th>β</th>
<th>t</th>
<th>p</th>
</tr>
</thead>
<tbody>
<tr>
<td>Step 1:</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Factor 1/Satisfaction with Time Use</td>
<td>.269</td>
<td>0.052</td>
<td>.448</td>
<td>5.18</td>
<td>.000***</td>
</tr>
</tbody>
</table>

Note: $R^2 = .201$, adj. $R^2 = .193$, $F_{1,107} = 26.855$, $p < .001$
$p < .05$. ** $p < .01$. *** $p < .001$

**Course persistence.** Independent samples $t$-tests were run on 16 variables, to see if there would be any significant associations with course completion. The variables were the three Factors (Satisfaction with Time Use, Evaluating and Monitoring, and Setting Intentions), the TMBS total score, the three TMBS subscales, the six times of day, hours of sleep, seven hours of sleep or not, and ratio of total clicks to the course average. To account for family-wise error, a Bonferroni correction was used, for a required $p < .0026$. The only variable that showed a significant difference in means to this level between the six students who did not complete the course and their peers was the Mechanics subscale of the TMBS ($n = 106, t = -3.31, p = .001$). The mean score on the five-point scale for students who did not finish the course was 2.92 ($SD = .73, SEM = .30$), while it was 3.84 ($SD = .67, SEM = .07$) for those who did.

Binary logistic regression on the course completion outcome showed no predictive significance from any of the following demographic factors: course, course background, enrollment status, whether fully online or not, hours per week of work, hours per week of dependent care, first-generation status, age, and gender. None of the independent variables were predictive either.
When other variables were not controlled, the Mechanics scale of the TMBS did have predictive value (Wald statistic = 7.815, \( p = .005 \), \( B = 1.918 \) [1.774, 2.6100], \( \text{Exp}(B) = 6.804 \)). However, after controlling for course background, most recent GPA, course load, course, age, gender, and race/ethnicity, the odds of the score on the Mechanics scale decreased below significance for all except most recent GPA (Wald statistic = 3.915, \( p = .005 \), \( B = 2.343 \) [1.022, 106.015], \( \text{Exp}(B) = 10.411 \), \( p = .048 \)).

**Grades.** Given the small range (2.0 to 4.0) and the predominance of grades 3.7 and 4.0, final grade was not promising as an outcome variable. Cohen (1992) recommends a minimum sample size of 76 to detect a medium effect in multiple regressions with three predictors, and a minimum of 84 with four, when alpha is set at .05. Given a sample size of 81 for grades, it should have been possible to detect medium effects at best. Further, for first-generation students, the sample size decreased to 28.

When regressed on final grade, none of the three new factors contributed anything to the model, either for the sample overall or for the first-generation group (in fact, \( R^2 \) was negative in most cases). The same was true when models with times of day, hours of sleep, ratio of total clicks to course average, and the original TMBS measures were tested. The best model for grades (\( R^2 = .077 \), adj. \( R^2 = .064 \), \( F_{1, 72} = 6.024 \), \( p = .017 \)) had one predictor, and it was negative: percent access from 6 pm to midnight (\( B = -.011 \), \( SE = .004 \), \( \beta = -.278 \), \( t = -2.454 \), \( p = .017 \)). The unstandardized coefficient is too small to make any practical difference. This model was not a significant predictor for first-gen students alone, nor were any of the other variables tried on final grades.

Another predictor, average number of leisure hours online, approached significance as a negative predictor of grades. However, the contribution was too small
to have any practical impact on grades (for the sample overall, $B = -.013, p = .076$; for first-gen students, $B = -.020, p = .066$).

Regression results were more significant when a composite of final grade and course completion (non-completion counted as a C-) was used as the outcome variable. As shown in Table 6, the best model had three predictors: Satisfaction with Time Use (positive predictor), number of time management tools (negative predictor) and Mechanics (positive predictor). This model accounted for about 15% of the variance.

Table 6

*Best Model for Predictors of Grade and Course Completion (n = 87)*

<table>
<thead>
<tr>
<th>Step and predictor variable</th>
<th>$B$</th>
<th>SE $B$</th>
<th>$\beta$</th>
<th>$t$</th>
<th>$p$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Step 1:</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Satisfaction with Time Use, Number of Time Management Tools</td>
<td>-.113</td>
<td>.041</td>
<td>-.283</td>
<td>-2.72</td>
<td>.008*</td>
</tr>
<tr>
<td>TMBS Mechanics subscale</td>
<td>.316</td>
<td>.111</td>
<td>.297</td>
<td>2.85</td>
<td>.006*</td>
</tr>
</tbody>
</table>

Note: $R^2 = .158$, adj. $R^2 = .137$, $F_{1,79} = 7.332, p < .001$
$p < .05$. **$p < .01$. ***$p < .001$

Study Times of Day

While they did not yield any significant results in this study, daily patterns of course access were interesting to see. The pattern for all students combined (each has a different color) is shown in Figure 3. Highest times of course access overall were from
mid-day to 11 pm. Midnight to 6 am accounted for less than a tenth of student access time, while access for all other time segments was pretty evenly divided. Once binned into six-hour segments, they showed a striking evenness from 6 am to midnight, as shown in Figure 4.

Figure 3. Combined Daily Student Patterns of Course Access

$N = 103$. Each color represents a different student’s activity on the course web site.
Figure 4. Percentage of Student Access to Course Web Site

Each bin represents a six-hour period. 1 starts with midnight, and 4 ends with midnight. Each color represents one student (N=103) (only a few de-identified IDs are shown).
Group Differences

To explore distribution across groups, independent sample Kruskal-Wald and Mann-Whitney tests were run for each group against the grade, course persistence and college wellbeing variables, as well as the combined outcome variable and the three variables identified in factor analysis. Most results were insignificant ($p < .1$). There were some important differences between first-generation students and their peers, however, in terms of age and work. First-gen students were older ($t_{106} = 2.414$, $p = .017$). They worked an average of 13 hours a week more than their peers ($t_{82} = 2.797$, $p = .006$). There was a strong negative association between hours of work for pay and hours of sleep ($p < .001$). However, when means comparisons were made for weekly hours of obligations to jobs, and nightly amounts of sleep, there was a significant difference for first-generation students: compared to their peers, they worked 13 hours more per week at paying jobs. When dependent care was added to the mix, they were obligated, on average, to two hours per day more non-academic work. While nearly 68% of their peers reported getting at least seven hours of sleep per night, only 50% of first-gen students reported this. More detail on how first-generation students compared to their peers are in Appendix F.

The regression models for predicting outcomes were similar for first-generation students and the overall sample. For college wellbeing, Satisfaction with Time Use was the sole predictor for first-gen students, as shown in Table 7. The same was true for the sample as a whole. For combined grade/course completion outcome, number of time management tools negatively predicted the combined grade/course completion outcome.
for the first-gen group, as it did for the sample overall. In the first-gen model, though, as shown in Table 8, Satisfaction with Time Use replaced the second predictor, Mechanics.

Table 7

*First-Gen: Best Model for Predictors of College Wellbeing (n = 40)*

<table>
<thead>
<tr>
<th>Step and predictor variable</th>
<th>B</th>
<th>SE B</th>
<th>β</th>
<th>t</th>
<th>p</th>
</tr>
</thead>
<tbody>
<tr>
<td>Step 1:</td>
<td>.348</td>
<td>0.071</td>
<td>.623</td>
<td>4.905</td>
<td>.000***</td>
</tr>
<tr>
<td>Factor 1/Satisfaction with Time Use</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note: $R^2 = .388$, adj. $R^2 = .372$, $F_{1,38} = 24.059$, $p < .001$

* p < .05. ** p < .01. *** p < .001

Table 8

*First-Gen: Best Model Predicting Grades & Course Completion (n = 31)*

<table>
<thead>
<tr>
<th>Step and predictor variable</th>
<th>B</th>
<th>SE B</th>
<th>β</th>
<th>t</th>
<th>p</th>
</tr>
</thead>
<tbody>
<tr>
<td>Step 1:</td>
<td>-.148</td>
<td>0.062</td>
<td>-.386</td>
<td>-2.39</td>
<td>.024*</td>
</tr>
<tr>
<td>Number of time management tools</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Step 2:</td>
<td>.348</td>
<td>0.138</td>
<td>.456</td>
<td>2.181</td>
<td>.018*</td>
</tr>
<tr>
<td>Factor 1/Satisfaction with Time Use</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note: $R^2 = .158$, adj. $R^2 = .137$, $F_{1,79} = 7.332$, $p < .001$

p < .05. ** p < .01. *** p < .001

To test for possible interactions between first-gen status and non-academic obligations with success, plots of estimated marginal means in general linear models
were examined. None of the interactions reached significance, even to alpha 1.0. With a higher number of participants, however, some could have been significant, based on the intersection of means plots. The two described below are good examples.

One unexpected difference was that first-gen students were more likely to agree with the statement from the CSSWQ “other students here like me as I am” than continuing-gen students. The belief that students are liked for themselves may have a differential impact on first- and continuing-generation students when it comes to grades. As shown in Figure 5, first-gen students showed a linear decline in grade based on how strongly they agreed that other students liked them for who they were. Those who neither agreed nor disagreed with the statement scored slightly above the grand mean, and those who agreed scored slightly below it, while those who strongly agreed that they were liked for who they were were scored lowest. For continuing-generation students, neutral students scored slightly below the grand mean; the highest grades, 3.8, were for students who agreed that they were liked for who they were; and grades for students who strongly agreed were about halfway between the mean of 3.7 and their high score of 3.8. None of these results reached alpha .05.

Another potential interaction is how first-generation status may affect the relationship between course background and grade. As shown in Figure 6, Continuing-generation students (red) showed a somewhat linear progression from lowest grade with no background, to highest grade, when the student expected the course to be mostly review. Conversely, first-generation students (blue) with the highest grades had no background. First-generation students’ values for some, average, more, and mostly review showed a rising linear trend, but they stayed much closer to the grand mean than their peers when
they had stronger backgrounds in the course subject. Since only six students reported having no course background, these numbers, standing alone, are not significant. Still, they could indicate a pattern worth investigating further.

Figure 5. Agreement with “Other students here like me as I am” vs. Grade

First-generation students (n=40) in blue; continuing-generation students (n=68) in red
Figure 6. Course Background vs. Final Grade, Based on First-Gen status

First-generation students (n=40) in blue; continuing-generation students (n=68) in red
Chapter IV
Discussion

This investigation tested the continuing validity of self-report time management measures in the context new learning analytics measures and changing conditions for adult learners \( n = 109 \) enrolled in ten college and graduate level courses at a continuing education school in a large northeastern U.S. university.

Independent self-report variables included an established measure of time management behavior, a new self-report measure, and answers to individual questions about hours of sleep, multitasking, and use of time management tools. Daily activity patterns were extracted from log data.

Academic success was measured with three dependent variables: self-reported final course grades, self-reported college wellbeing, and course persistence as seen in log data. There was too little variability in grades and course persistence to support the low power of the small sample size, but when grades and course persistence were combined into a single variable, time management predictors emerged. Questions, predictions, and findings were as follows:

1. Does time management account for a significant amount of variance in grades, college wellbeing, and course completion? Findings supported the prediction that it would: the number of time management tools used (negative) and the Mechanics subscale of the TMBS accounted for about 20% of final grade and course persistence, while the Satisfaction with Time Use factor from the factor
an analysis accounted for nearly 16% of college wellbeing.

2. Which time management factors are the best predictors? Study times of day, adequate sleep, regular study, reduced leisure time online, and not multitasking were expected to be strong predictors. Instead, the best overall predictor of college wellbeing (and a key predictor of grades as well for first-gen students) was Satisfaction with Time Use. For grades and course outcome, number of time management tools used was a negative predictor, and the TMBS’ Mechanics subscale was a positive predictor.

3. Can new self-report questions and variables drawn from course log data improve on an established and time-tested self-report measure? LMS data, in its ability to pinpoint study times of day and regularity, had seemed likely to improve on self-report. Instead, old and new self-report measures were most predictive: the new Satisfaction with Time Use measure, the Mechanics subscale of the TMBS, and a new question on time management tool use.

4. Were there differences in outcomes and time management practices for first-generation students, given larger competing demands on their time from work and dependents? While work and dependent care did demand much more of first-generation students’ time than that of continuing-gen students, there were no differences in college wellbeing, grades or course outcome. The Satisfaction with Time Use subscale replaced Mechanics as a predictor of grade and course outcome for first-gen students. Also, there was an interaction between gender and first-gen status on course completion.

A few findings require more discussion and context. First, while Factor 1, the
new self-report Satisfaction with Time Use measure, was the predictor in the best model for college wellbeing, TMBS questions also had predictive value when regressed separately. Placing the TMBS and its subscales in stepwise regression on college wellbeing yielded a model with the TMBS accounting for nearly 15% of the variance in college wellbeing (B = .335, SE = .078, $R^2 = .147$, $F_{1, 107} = 18.44$, $p < .001$). Combined with the Mechanics subscale and number of time management tools predicting grades and course outcome, this indicates that old as well as new self-report measures are still effective predictors.

The lack of strong results for study times of day, sleep, multitasking and leisure hours online was surprising. None of the study times of day predicted final grade or college wellbeing when entered stepwise into regression. There might have been insignificant power to detect the impact of times of day, or more granular day divisions might have been needed. Two-way ANOVA of hours of sleep, frequency of multitasking, and leisure hours online versus college wellbeing also yielded no significant main effects results to alpha .05 with Bonferroni adjustment for multiple comparisons. The same was true when grade alone, and grade with and course outcome, were the dependent variables.

There were a few differences in findings for first-generation students. Those in this study spent almost two hours per day more at paying jobs than their peers, fewer of them got at least seven hours of sleep a night. While their peers got a few more A’s and A-’s (95.5%, versus 92.1%), they also got more C’s (4.4%, versus 2.5%). The lowest grade any first-gen student got was a C+, while several of their continuing-gen peers got C’s. Future research may investigate what behaviors and attitudes support first-gen
students’ ability to achieve similar academic success with less time.

Two interactions involving first-generation status show possible directions for future research. The first interaction, which did not reach significance, was between course background and first-generation status. In answer to the question “how much background do you have for this course compared to your peers,” students for whom at least one parent or guardian had gone to college showed a somewhat linear progression in the expected direction. The lowest grades, well below the grand mean, corresponded to the answer “no background,” while the highest grades, well above the grand mean, were associated with the answer “this course will be mostly review for me.” First-gen students showed the opposite trend. The highest grade for first-generation students corresponded to the response “no background.” Grades corresponding to “some”, “average”, “more than other student in this class”, and “mostly review” responses showed more of a rising linear trend, though they stayed closer to the grand mean than scores for continuing-gen students. One possible explanation is that students whose parents did not attend college may be more used to facing difficulty and more resilient to challenges. Continuing-generation students may be more likely to expect good grades, even with background in a subject, and respond to difficulty by retreating rather than working harder. An explanation for why the first-gen students did less well when their backgrounds were stronger could be that, having more demands on their time, they prioritize their academic work according to how much effort they think it will need.

A second interaction, again below significance but notable, was that first-gen students were more likely to agree with the statement “students here like me as I am” than their peers (this was significant to \( p = .01 \), but once a Bonferroni correction was
added for family-wise error among the 16 CSSWQ variables, alpha moved to .006, and the result lost significance) and they showed a linear decline in grade based on how strongly they agreed with the statement. This relationship was not seen in continuing-generation students. Theoretically, this could relate to the differential impact of course background. Students who strongly identify as first-generation may feel less comfortable with how they relate to continuing-generation students, but stronger identification with being first-gen may be associated with increased resilience and understanding that success comes with hard work. More affiliation, conversely, may correlate with first-generation students who do not strongly identify as such. These students may correspondingly have less of the resiliency that first-gen status may bring. It would be interesting to test this theory with a larger sample, using measures of resilience, grit, prioritization and social group identification as predictors of grades.

One unanticipated finding, also related to demographics, but not related to the study goals, deserves notice. When a two-way ANOVA was run on race, gender and first-generation status versus course completion, there was a significant \( (F_{7, 80} = 7.503, p < .001) \) relationship between race and course completion. Of the 106 students for whom course completion data was available, six did not finish their courses; five of these students reported the race or ethnicity they identified with. One identified as White, and one as Hispanic. Three identified as Black, which was surprising since only six Black students had enrolled in the study. The estimated mean course level completion for White students was 99%; for Hispanic students, .93%; and for Black students, 50%. The difference in completion rates could have been a function of the course, rather than race. All four students who did not identify as White and did not complete their courses were
taking Quantitative Reasoning (QR). QR had a smaller proportion of students with A’s and A-minuses ((73.1% versus 78.8%) and a higher proportion of C’s and C+’s (11.5% versus 6.3%) than study courses overall, indicating that grading was probably stricter in this class. QR was also the largest course in the study, with over 250 students, so it might have been harder to feel a connection to the instructor or TA’s, or get extra help. Another possible explanation could be that White and Asian students who were uncertain about being able to finish the course did not enroll in the study in the first place. Even if race did play a role in the difference in course completion rates, it is not possible to draw any conclusions from this study, given the very small sample. Still, as noted in Chapter 1, Black students have a much lower college persistence rate nationally than their peers.

Further research is needed in this area.

There were some major differences in the demographics of the study sample versus the U.S. postsecondary school population overall. The largest difference was part-time status: 91.7% of study participants were taking 3 courses or fewer, while the national rate for part-time students in 2016 was 38.9% (U.S. Department of Education, 2017a). There was also a marked difference in age: the study had less than half the national percentage of part-time students who were young adults, and more than twice the national percentage for adults in their early thirties and older (U.S. Department of Education, 2017f). The percentage of women enrolled in the study (73.4%) was larger than the national figure (56.5%); the percentage of White and Asian students (73.1%) was also larger than the national figure (64.4%) (U.S. Department of Education, 2017a). Six of the 109 study participants did not report their race or ethnicity.

In sum, this study is not representative of the U.S. postsecondary population.
Participants were older, more likely to be female, more likely to be White or Asian, and less likely to be Black or Hispanic than U.S. postsecondary students overall. Age differences likely relate to the continuing education focus of the school.

Based on this study, there may be a need to revisit the way human subjects research guidelines are applied to protecting student online data. The school gave solid support for this project, but obtaining the data for this study took almost a year, taking into account time to IRB approval and time needed to de-identify the data. This was true even with people all over the university willing to help, from navigating the IRB process (with help from kind and knowledgeable IRB staff) to collecting, de-identifying and pre-processing the data. The registrar declined to provide grades or other objective information, even with students’ permission, so the study had to rely on self-report.

Protecting student privacy is critical, but given that students’ data is their own property, and should be able to share it. Students do this every day when they visit websites, but in the school context, they are not given the choice.

This study was purely correlational, so no conclusions about causation can be drawn. Still, based on the findings about time management satisfaction and the CSSWQ, a significant connection between time management support and student wellbeing exists. The current results suggest first-generation students may have a lot to teach their peers. It is hoped this study may inspire further conversation among higher education academic support professionals about how time management relates to success, and spark further research.
Limitations and Future Directions

The study results offer a glimpse into how much there is to be learned about the relationship between time management and adult learners’ success in terms of wellbeing, grades and course persistence. There were a few findings significant to alpha .05. Still, there were significant limitations.

First, the study is correlational. Causal relationships cannot be determined.

Second, while they were administered in two separate surveys at different times in the semester, the self-report measures were cross-sectional, representing single points in time. Also, the CSSWQ was administered one month into the semester, so wellbeing scores did not reflect mid-to-late semester student experiences. In addition to the usual problems with cross-sectional data, stressors vary during the school semester. Due to mood-congruent memory, a currently depressed student is more likely to remember and report having had a depressed state of mind in the past, even if the memory is inaccurate.

Third, only about 10% of students invited to join the study participated; over 20% of the participants who began the study did not complete the follow-up survey; and Canvas log data was missing for all six students in one course. Time of day computations were not possible for several students who either reported multiple time zones, or did not report time zones at all. All of these factors resulted in a smaller than optimal sample sizes for various calculations.

The sample size issue is especially important when it comes to factor analysis. This study had 109 participants overall, and 87 participants who completed both surveys. Both numbers are similar to the 90 participants Britton & Tesser (1991) used for their factor analysis of 30 survey items. Hellsten (2012) asserted that the results of this and
another factor analysis might be unstable, however, given the large ratio of items to
participants. Had it been possible to recruit 300 to 600 participants as planned, the
commonly referenced ten subjects per item suggested ratio could have been achieved.

Another issue was the possibility of Type II error: there was no way to detect
small effect sizes with 109 cases. Based on Cohen’s (1992) suggestions for detecting
varying effect sizes at Power = .80 and alpha = .05, even with only two predictors, a
sample size of 481 would have been needed to detect a small effect in multiple regression.
Reducing the number of variables with factor analysis did improve the possibility of
detecting medium to large effect sizes.

The low response rate raises the possibility of a fourth limitation, selection bias.
In particular, students who managed their time well might have been more inclined to
volunteer, and more likely to follow through with surveys, than students who did not
manage their time well, or who were juggling multiple demands on their time and wisely
ranked the study as a low priority. On the other hand, it is possible students who were
struggling with time management were most interested in the study, or were most likely
to welcome the distraction of filling out a survey instead of addressing school work.
Eighty percent of the participants completing the fall survey also completed the follow-up
survey in January. The 22 that did not could have been extreme procrastinators, under
major time constraints, or had other attributes related to time management. Luckily,
some analyses required only the fall survey, and there was LMS data for the full semester
for all but six participants.

A fifth limitation is generalizability. The population for this study was students
taking on-line or hybrid classes at a large continuing-education school in the Northeast.
Results may not generalize to schools that are smaller, enroll a more traditional student population, are located in other parts of the country or world, or have different admissions standards, teaching methods, facilities or academic support offerings, to name a few variables.

Even within the studied school, the LMS data may indicate different things in different courses. Researchers have found that data from learning analytics alone may not generalize well across courses as predictors of academic performance (Conijn et al., 2017). Combining Canvas data with self-report measures, and using a wide variety of courses, may help ameliorate this within-school generalizability limitation.

The self-report nature of many measures in the study brings a seventh limitation: response bias. Students may respond to the survey in ways that they anticipate the researcher expects, or that will make them look good. Students may not have accurate memories of their own experiences, or assessment of their own abilities. It is also possible that a student will misread a question. Still, by combining self-report with objective measures, using measures that have been tested and validated in other studies, and using a variety of measures, it is hoped that the survey will give a relatively accurate view of students’ time management skills, attitudes and behaviors, as well as their states of well-being.

An eighth limitation is the reliability of LMS data collection and reporting. While every effort was made to ensure that proper time zones were calculated before determining time of day in the log data, and ambiguous data was excluded from time analysis, some students might have self-reported that they were in time zones they actually were not in, or may have moved through several time zones over the course of
the semester. In addition, it is possible that LMS did not log students’ access from some types of devices. Data reliability issues like this are likely to arise in most learning analytics research, at least until LMS’s are optimized and more institutional data is available for corroboration.

Next, for the online data collection, a key limitation is the inability of course management websites to detect when students are multitasking, or have logged into the course website but are doing something else altogether. These web platforms also cannot detect when students are working off-line. Because some study session ID’s repeated over multiple days, it was impossible to determine how long each session actually was.

A tenth limitation was that final course grades and course completion were self-reported, and there was little variance in either of these outcome variables. Over eighty percent of the 71 students answering the final grade question reported receiving an A or A-, while a handful each of students reported C’s or did not complete the course. The lack of variability in grades and course completion may relate to the selection bias, or to self-promotion bias. Knobbout and van der Steppen (2017) found that the 38% of students opting in to share their data from a learning management system earned higher final grades (average 5.1), than the 62% who did not opt in (average 4.3). Given only 7.7% of the possible pool of 1133 students participated and followed through to report their grades, and grades were self-reported, these impacts may be more marked in the current study.

Another important limitation was the multilevel nature of the data, which this study did not account for. Given only 10 courses for level 2 variables, multilevel modeling would not have been advisable (see O’Dwyer & Parker, 2014, p. 7).
Finally, multitasking aside, this study did not assess students’ efficiency with academic work. Some students are easily distracted, and can spend hours in the library while accomplishing little. More focused students may need less time to complete their work. It would be interesting to see what role attention surfeits and deficits have on correlations between time management and student success. Future research could monitor students’ study habits, track their learning or productivity, or differentiate between students with attention challenges and students with better focus and flexibility.

Future research can build on the results of this study, in addition to the ideas noted above. As qualities of time management skills, attitudes, and behaviors that contribute to student success emerge, research can examine the efficacy of interventions in promoting these qualities. The results can contribute to the growing field of learning analytics. Finally, with validation on larger and different populations, a new, streamlined self-report time management measure may result.
References


IBM Corp.


O’Dwyer, L. M., & Parker, C. E. (2014). *A Primer for analyzing nested data: Multilevel modeling in SPSS using an example from an REL study (REL 2015-046)*. Washington, DC.


Additional Works Consulted


Appendix A. Web Site Survey of College Time Management Resources

The first ten hits from a November 22, 2017 search on Google for “college academic support programs” are in Table A1. Based on a search of their web sites, nine out of the ten offered time management support or advice. On November 25, an identical search yielded the schools listed in Table A2. A deeper search of their websites yielded details about the schools’ time management services that are outlined in the table.

Table A1

Results of Google Search for College Time Management Offerings

<table>
<thead>
<tr>
<th>School</th>
<th>Time Management Support?</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wheelock College, Boston, MA</td>
<td>Yes</td>
</tr>
<tr>
<td>University of the Pacific, Stockton, CA</td>
<td>Yes</td>
</tr>
<tr>
<td>University of Massachusetts – Boston</td>
<td>Yes</td>
</tr>
<tr>
<td>McDaniel College, Westminster, MD</td>
<td>Yes</td>
</tr>
<tr>
<td>Antioch College, Yellow Springs, OH</td>
<td>NO</td>
</tr>
<tr>
<td>University of Southern California – Santa Barbara</td>
<td>Yes</td>
</tr>
<tr>
<td>Oberlin College, Oberlin, OH</td>
<td>Yes</td>
</tr>
<tr>
<td>Lafayette College, Easton, PA</td>
<td>Yes</td>
</tr>
<tr>
<td>City University of New York</td>
<td>Yes</td>
</tr>
<tr>
<td>University of Maryland, College Park, MD</td>
<td>Yes</td>
</tr>
</tbody>
</table>
Table A2

Time Management Offerings Mentioned on 10 College Web Sites

<table>
<thead>
<tr>
<th>School</th>
<th>Workshop or Topic in First Year Seminar, Bridge Program or Tutorial?</th>
<th>Tutoring, Mentoring, Coaching or Advising</th>
<th>Tip Sheets or Web Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wheelock College, Boston, MA</td>
<td>Bridge Program</td>
<td>Peer Tutoring; Office of Academic Assistance Success Coaching</td>
<td>Yes</td>
</tr>
<tr>
<td>University of the Pacific, Stockton, CA</td>
<td>Workshops; Productivity and Time Management course and certificate Workshop</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>University of Massachusetts – Boston</td>
<td>Workshops; First Year Seminar topic No</td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td>McDaniel College, Westminster, MD</td>
<td>Workshops; First Year Seminar topic No</td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td>Antioch College, Yellow Springs, OH</td>
<td>Academic Performance Tutorial No</td>
<td>No</td>
<td>Yes (also blog entries)</td>
</tr>
<tr>
<td>Cornell College, Mt. Vernon, Iowa</td>
<td>Oberlin College, Oberlin, OH</td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td>Lafayette College, Easton, PA</td>
<td>Workshops; first topic in First Year Seminar Workshops</td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td>Bronx Community College, Bronx, NY</td>
<td>University of Maryland, College Park, MD</td>
<td>No</td>
<td>No</td>
</tr>
</tbody>
</table>
Appendix B. Participant, Subject and Requirement Breakdowns for Courses

Table B1

Participants and Course Topics (n = 109)

<table>
<thead>
<tr>
<th>Study Code</th>
<th>Course</th>
<th>Course N</th>
<th>Study n</th>
<th>Study %</th>
<th>Math &amp; Stats</th>
<th>Social Sciences</th>
<th>Physics &amp; CS</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Quantitative Reasoning</td>
<td>259</td>
<td>35</td>
<td>32.1</td>
<td>35</td>
<td></td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>Intermediate Statistics</td>
<td>79</td>
<td>18</td>
<td>16.5</td>
<td>18</td>
<td></td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>Abnormal Psych</td>
<td>66</td>
<td>14</td>
<td>12.8</td>
<td>14</td>
<td></td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>Financial Accounting</td>
<td>116</td>
<td>13</td>
<td>11.9</td>
<td>13</td>
<td></td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>Social Psych</td>
<td>87</td>
<td>9</td>
<td>8.3</td>
<td>9</td>
<td></td>
<td></td>
</tr>
<tr>
<td>7</td>
<td>Linear Algebra</td>
<td>116</td>
<td>6</td>
<td>5.5</td>
<td>6</td>
<td></td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>Intro to Physics</td>
<td>202</td>
<td>5</td>
<td>4.6</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>8</td>
<td>Relationship Psych</td>
<td>94</td>
<td>5</td>
<td>4.6</td>
<td>5</td>
<td></td>
<td></td>
</tr>
<tr>
<td>9</td>
<td>Web Design</td>
<td>79</td>
<td>2</td>
<td>1.8</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>10</td>
<td>Pre-calculus</td>
<td>35</td>
<td>2</td>
<td>1.8</td>
<td>2</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total #</td>
<td></td>
<td>1133</td>
<td>109</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total %</td>
<td></td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
<td>56.0%</td>
<td>37.6%</td>
<td>6.4%</td>
</tr>
</tbody>
</table>

Table B2

January Survey Participants (n = 87), with Course Topics

<table>
<thead>
<tr>
<th>Study Code</th>
<th>Course</th>
<th>Course N</th>
<th>Study n</th>
<th>Study %</th>
<th>Math &amp; Stats</th>
<th>Social Sciences</th>
<th>Physics &amp; CS</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Quant. Reasoning</td>
<td>259</td>
<td>27</td>
<td>32.0</td>
<td>27</td>
<td></td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>Intermediate Statistics</td>
<td>79</td>
<td>11</td>
<td>12.6</td>
<td>11</td>
<td></td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>Abnormal Psych</td>
<td>66</td>
<td>13</td>
<td>14.9</td>
<td>13</td>
<td></td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>Financial Accounting</td>
<td>116</td>
<td>11</td>
<td>11.7</td>
<td>11</td>
<td></td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>Social Psych</td>
<td>87</td>
<td>8</td>
<td>9.2</td>
<td>8</td>
<td></td>
<td></td>
</tr>
<tr>
<td>7</td>
<td>Linear Algebra</td>
<td>116</td>
<td>4</td>
<td>4.6</td>
<td>4</td>
<td></td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>Intro to Physics</td>
<td>202</td>
<td>5</td>
<td>5.7</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>8</td>
<td>Relationship Psych</td>
<td>94</td>
<td>4</td>
<td>4.6</td>
<td>4</td>
<td></td>
<td></td>
</tr>
<tr>
<td>9</td>
<td>Web Design</td>
<td>79</td>
<td>2</td>
<td>2.3</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>10</td>
<td>Pre-calculus</td>
<td>35</td>
<td>2</td>
<td>2.3</td>
<td>2</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total #</td>
<td></td>
<td>1133</td>
<td>87</td>
<td></td>
<td>44</td>
<td>36</td>
<td>7</td>
</tr>
<tr>
<td>Total %</td>
<td></td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
<td>50.6%</td>
<td>41.4%</td>
<td>8.0%</td>
</tr>
</tbody>
</table>
Table B3

Sample Course Requirements

<table>
<thead>
<tr>
<th>Study Code</th>
<th>Course</th>
<th>Graded Course Requirements</th>
<th>Special Requirements for Graduate Students</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Quantitative Reasoning</td>
<td>Quizzes (2)</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Final Exam</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>Intermediate Statistics</td>
<td>Discussion Board</td>
<td>Weekly Problem Sets</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Weekly Quizzes</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Final project</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Midterm</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Final Exam</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>Abnormal Psychology</td>
<td>Study Pool</td>
<td>Term Paper (instead of Movie Paper)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Response Papers (5)</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Paper on Movie</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Midterm</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Final Exam</td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>Financial Accounting</td>
<td>Quizzes</td>
<td>Homework</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Final Exam</td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>Intro to Social</td>
<td>Discussion Board</td>
<td>5-Page Paper</td>
</tr>
<tr>
<td></td>
<td>Psychology</td>
<td>Exams (3)</td>
<td></td>
</tr>
<tr>
<td>7</td>
<td>Linear Algebra</td>
<td>Quizzes (2)</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Final Exam</td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>Intro to Physics</td>
<td>Course Participation</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Problem Sets</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Tests (3)</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Final Exam</td>
<td></td>
</tr>
<tr>
<td>8</td>
<td>Relationship Psychology</td>
<td>Discussion Board</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Papers (3)</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Writing Conference</td>
<td></td>
</tr>
<tr>
<td>9</td>
<td>Web Design</td>
<td>Projects (4)</td>
<td>Weekly Homework (ungraded)</td>
</tr>
<tr>
<td>10</td>
<td>Pre-calculus</td>
<td>Quizzes (3)</td>
<td>Weekly Problem Sets</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Final Exam</td>
<td></td>
</tr>
</tbody>
</table>

*Note:* Table is based on past syllabi; assignments may have changed in 2018.
Appendix C. Self-Report Survey Measures

Time Management Behavior Scale (adapted from the measure prepared by Lay and Schouwenburg (1993)*, which was based on measures by Macan et al. (1990) and Britton and Tesser (1991)).

Prompt: “For each item below, please select the answer that best describes you as you have been this semester.” Responses are on a scale from 1 (Strongly Disagree) to 5 (Strongly Agree).

Setting Goals and Priorities Subscale**

1. I review my goals to determine if they need revising or changing.
2. I break complex, difficult problems into smaller manageable tasks.
3. I set short-term goals for what I want to accomplish in a few days or weeks.
4. I look for ways to increase the efficiency with which I perform my school or work activities.
5. I review my daily activities to see where I am wasting time.
6. During a school or workday I evaluate how well I am following the schedule I have set down for myself.
7. I set priorities to determine the order in which I will perform tasks each day.

Mechanics Subscale**

8. I carry a notebook or use my phone to record notes and ideas.
9. I make notes to remind myself what I have to do.
10. I use a planner or calendar to keep track of my appointments.
11. I keep a daily log of my activities.
12. If I know I have to spend some time waiting, I bring along something I can work on.
13. I make a list of things to do each day***
Perceived Control of Time Subscale**

14. I find myself taking on too many tasks/responsibilities at one time. R*
15. I find myself overwhelmed by unimportant or trivial tasks. R*
16. I underestimate the amount of time it would take to complete tasks. R*
17. I feel in control of my time.
18. I am unable to say no when others ask me to take on additional responsibilities. R*
19. I believe there is room for improvement in the way I manage my time*** R*
20. I make constructive use of my time***

R* means reverse scored.


Satisfaction with Time Management Survey, Doing/Skill Subscale (Bisbee, 2016)

Prompt: “In the past month, how satisfied have you been with your ability to _______?”

Responses are on a scale from 1 (Strongly Disagree) to 5 (Strongly Agree).

1. Get started on big tasks
2. Focus on the task at hand
3. Switch tasks when appropriate
4. Get places early or on time
5. Plan ahead
6. Start assignments early
7. Finish assignments early or on time
8. Realistically estimate how long things will take
9. Say “no”
10. Deal with unexpected events
11. Follow chosen daily routines
12. Keep track of obligations
13. Follow through on commitments
College Student Subjective Wellness Questionnaire (Renshaw & Bolognino, 2014, 2016)*

Prompt: “For each item below, please select the answer that best describes you as you have been this semester.” Responses are on a scale from 1 (Strongly Disagree) to 5 (Strongly Agree).

Academic Satisfaction Subscale

1. I have had a great academic experience at (name of college).
2. I am happy with how I’ve done in my classes.
3. I am satisfied with my academic achievement since coming to (name of college).
4. I am pleased with how my college education is going so far.

Academic Efficacy Subscale

5. I am a hard worker in my classes.
6. I am a diligent student.
7. I am an organized and effective student.
8. I study well for my classes.

School Connectedness Subscale

9. I feel like a real part of (name of college)
10. People at this school are friendly to me.
11. I can really be myself at this school.
12. Other students here like me the way I am.

College Gratitude Subscale

13. I am so thankful that I’m getting a college education.
14. I am grateful to the professors and other students who have helped me in class.
15. I feel thankful for the opportunity to learn so many new things.
16. I am grateful to the people who have helped me succeed in college.

Follow-Up Survey Questions

- What was the outcome for this course? (Completed, Withdrew or Dropped)
- What was your final grade in the course? (Select letter grade, or Don’t know)
- On average last semester, how often did you multitask while you were doing course work, watching a lecture or attending class or section? (Rarely or never, Less than half the time, About half the time, Most of the time, Always)
- On average last semester, about how many hours per week did you work at a job for pay?
- On average last semester, about how many hours per week did you care for a child, sibling, parent, or other dependent?
- On average last semester, about how many leisure hours per week did you spend online? (Note: this includes things like texting, emailing, surfing the Internet, shopping, playing games, using social media, or watching videos, movies or TV. It does not include course work or work for a job.)
- Which of the following tools did you use last semester to manage your time? (Check all that apply)
  - Alarms to wake up
  - Alarms for things other than waking up
  - Timers
  - Online calendars or planners
  - Paper calendars or planners
  - Email reminders
  - Internet site blockers
  - Online time trackers
  - Online project management tools
  - Wristwatch
  - Smart watch
  - Other ________________________

Note: Options for the three “how many hours per week” questions were: None, less than 5 hours a week, 5 to less than 10 hours a week, 10 to less than 20 hours a week, 20 to less than 35 hours a week, 35 to 45 hours a week, and 45 hours or more a week. On a numerical hourly scale adapted during data analysis, they were coded as 0, 3, 8, 15, 28, 40, and 50.
Appendix D. Comparison of Change Scores on SSTS, 2016 Study

Table D1

*Pre/Post Change Scores on SSTS by Group with ANOVA, 2016 Study*

<table>
<thead>
<tr>
<th>Subscale</th>
<th>Workshop M (SD)</th>
<th>Comparison M (SD)</th>
<th>Sample M (SD)</th>
<th>CI for 95% Sample M</th>
<th>p-value for ANOVA</th>
<th>Hedge’s g</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>N = 31</td>
<td>N = 76</td>
<td>N = 107</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Being/Balance</td>
<td>6.13 (7.36)</td>
<td>1.67 (7.03)</td>
<td>2.96 (7.13)</td>
<td>1.55, 4.33</td>
<td>.004**</td>
<td>0.621</td>
</tr>
<tr>
<td>Doing/Skill</td>
<td>8.03 (5.83)</td>
<td>2.16 (6.28)</td>
<td>3.8 (6.69)</td>
<td>2.58, 5.14</td>
<td>.000***</td>
<td>0.947</td>
</tr>
</tbody>
</table>

p < .05.  ** p < .01.  *** p < .001

Table D2

*Follow-Up Change Scores on SSTS by Group with ANOVA, 2016 Study*

<table>
<thead>
<tr>
<th>Subscale</th>
<th>Workshop M (SD)</th>
<th>Comparison M (SD)</th>
<th>Sample M (SD)</th>
<th>CI for 95% Sample M</th>
<th>p-value for ANOVA</th>
<th>Hedge’s g</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>N = 24</td>
<td>N = 63</td>
<td>N = 87</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Being/Balance</td>
<td>5.14 (8.04)</td>
<td>-0.682 (8.71)</td>
<td>1.00 (8.92)</td>
<td>-0.90, 2.90</td>
<td>.004**</td>
<td>0.518</td>
</tr>
<tr>
<td>Doing/Skill</td>
<td>6.08 (7.35)</td>
<td>1.94 (6.43)</td>
<td>3.08 (6.91)</td>
<td>1.61, 4.55</td>
<td>.011*</td>
<td>0.801</td>
</tr>
</tbody>
</table>

p < .05.  ** p < .01.  *** p < .001
Appendix E. Data Analysis Procedures

Analysis procedures are detailed below. Survey data processing is covered first, then LMS data processing. Reliability and factor analysis are then discussed, followed by group distributions and correlations. Regression is not detailed here, as it is given more attention in Chapter 3.

Survey Data Processing

Survey 1 responses were downloaded into SPSS (2017) and reviewed for completeness and duplicates. There were seven incomplete surveys. Six were from responders who subsequently submitted complete surveys, and the seventh was barely started. Deleting these left 109 valid cases. Manipulation checks revealed that one participant who had given opposite responses to similar questions on ability to estimate time had actually marked every item in the SSTS the same, “very dissatisfied”. Entries on other measures looked valid, and the student could have identified as not being satisfied with anything. The survey was retained in the data. All cases were assigned simple numeric ID’s, and several variables were converted to binary or ordinal scales for ease of analysis.

In RStudio (2009), the survey results were reviewed to confirm that there was one row per participant, and that all the variables from the original survey were present. Where appropriate, data was assessed for outliers, linearity, heteroscedasticity, and multicollinearity. Since there were over 100 participants, the central limit theorem was applied, and skew and kurtosis were ignored.
LMS Data Processing

LMS data was processed with RStudio (2009) for larger files, and SPSS (2017) for files of a more manageable size. A third party in the university’s research unit de-identified the semester’s Canvas data from the ten courses, and assigned an anonymous identifier to each study participant that was linked to the student’s self-report survey data. It was possible to match 103 of the 109 anonymous identifiers to surveys. The remaining six were all the students in Linear Algebra, so there may have been a course to id mapping problem for these. It was not possible to retrieve them.

Given a short timeframe as well as the difficulty of transferring multiple variables from R to SPSS, the decision was made to look at overall timing patterns based on clicks, without distinguishing between the nature of each activity (taking a quiz, submitting an assignment, participating in a discussion, etc.). Canvas uses Universal Coordinated Time (Greenwich Mean Time), and students had completed surveys all over the world, so it was necessary to convert each participant’s timestamps to their time zone. Data was sorted into 13 files, one for each time zone. Most zones used daylight savings time, and these were sub-sorted pre- and post- date of time switch, which was either November 4 (United States, Canada and Buenos Aires) or October 28 (Europe). Canaberra had a November 7 switch, and there was no daylight savings switch for Kolkata, Karachi, Muscat and Seoul. With the split files, SPSS’s Date and Time Wizard was used to convert the time zones, and extract the hours of the day for each one. First and last access dates had been saved earlier, and these were used as a check against time calculations and merges as the files were merged back together. For example, if timestamps for a U.S. student ended on November 3 in the adjusted file, while they had
ended in December originally, it was clear that the Standard Time portion of the data had been dropped, and needed to be retrieved from the original file. *(Note for anyone considering doing time zone conversion whom, like me, is new to big data: This process, and subsequent file merging, took quite a while, and SPSS crashed every few hours. It worked in the end, but there is probably an easier way using R’s lubridate package.)*

To replicate work of Zhang et al. (2018) on study times of day, click frequency by hours of day was binned into four categories: 12 am to 6 am, 6 am to 12 pm, 12 pm to 6 pm, and 6 pm to midnight. For each participant with accessible log data (*n* = 101), overall percentages of clicks were taken for each time period. While percentage of clicks at various times of day was the variable ultimately used, other variables from Canvas data were explored in earlier stages: overall clicks, a regularity of access measure, and a standard deviation of days measure. The overall number of clicks variable was likely to vary in meaning by course; if this variable is used in the future, each student’s number of clicks should be divided by their course’s mean. The regularity and standard deviation variables seemed too rough at this time to be reliable, and were deleted in the final analyses.

While not used in this study, data on course patterns was extracted that may be useful for future research. Histograms of daily and hourly access over the semester were printed. Patterns were identified. These were similar to the deadline-related pacing styles studied by Gevers et al. (2015), but rather than being deadline-based, they measure the distribution of course engagement over the full semester. In addition to early, late, steady, u-shaped and inverted u-shaped distributions, three categories were added for patterns of peaks: early/middle/late, early/middle, and middle/late. The data was
visually sorted based on the patterns that seemed to best apply histograms of students’ course engagement. Examples are in Figure E1. Figure E2 shows the distribution of patterns across the study sample. The most common pattern was steady access and peak in the middle (inverted U); the least common was early and late access (U-shape).

- **Pattern 1: Early Access**
- **Pattern 2: Late Access**
- **Pattern 3: Steady Access**
- **Pattern 4: Inverted U**

*Figure E1. Sample Course Patterns*
Survey Reliability Analysis

Before factor analysis, reliability of self-report measures was assessed in SPSS (2017). All scales and sub-scales had Chronbach’s alpha > .7. The following were flagged for possible removal to increase item to subject ratio:

1. “Increase efficiency” in the Goals and Priorities subscale of the TMBS/TMQ: the subscale would still have an alpha of .81 if “break down tasks” were deleted, and
The reliability would only be .01 lower, at .80, if “increase efficiency” were deleted. “Break down tasks” was kept, as it is a more concrete survey question.

2. “Underestimates the time it takes” in the Perceived Control of Time subscale of the TMBS/TMQ. Reliability would rise slightly, from .74 to .75, if the item were deleted.

3. Reliability for each of the 13 items in the Student Satisfaction with Time Scale was between .91 and .92. Given the current alpha of .92, it may make sense to drop some items. However, each item gives specific information about a different aspect of time management.

4. For the CSSWQ, all 16 items had reliability alphas between .86 and .87. Particularly where questions were very similar (e.g., “grateful to people at this school” and “grateful to professors and students”), it could make sense to delete some items.

5. “Great academic experience” in the Satisfaction subscale of the CSSWQ: alpha would increase from .75 to .79 if it were removed. Given the generality of the prompt, deleting it should not result in a lower information value for the scale.

6. “Thankful for the opportunity” in the Gratitude subscale of the CSSWQ: the subscale would still have an alpha of .80 if this were dropped. Since “thankful for education” is very similar, this may be an item to drop.

7. The Effort subscale of the CSSWQ had an alpha of .82. Dropping “hard worker” would lower it to .81. Given the similarity of “diligent” and “hard worker” and the benefits of shorter surveys, dropping it may make sense.
Factor Analysis

Factor analysis was ultimately conducted on data from Survey 1 only, as this data was ready earlier when there was time available to run the analysis, and also because the \( n \) for Survey 2 (87) was smaller. Subsequent tests with the Survey 2 and LMS data, however, did not change the results.

Since there was still a relatively small (109) sample size for factor analysis, strict criteria for factor extraction were applied. Following recommendations of Field (2013, pp. 683-684, s. 17.5.2.1) for sample sizes between 100 and 200, only variables with loadings are over .512 were extracted (Field, p.681, citing Stevens, 2002). Each factor was also required to have at least two loadings over .6, and all variables with no correlations reaching approximately .4 were deleted. Comparison testing was run in PAC with oblimin rotation to ensure PCA with Varimax, which is technically component rather than factor analysis, returned similar results. There were only small differences, and the more commonly used PCA with Varimax rotation was selected.

A first rotation on all TMBS and SSTS variables (33 in all) returned 8 factors, accounting for 66.5% of the variance. Over several further iterations, items were deleted when any of the following applied: they did not load as high as the others, did not contribute anything very unique to the analysis, or seemed ambiguous, and did not decrease KMO much when removed. For example, the TMBS “underestimate time” item was similar to the SSTS question on satisfaction with ability to estimate how long things will take. The TMBS item on efficiency did not load as high as others, and another item was similar. The the “room to improve” item was also deleted, because students lacking awareness of poor time management may score high, while students with better self-
awareness and higher standards could score lower.

Ultimately, a 15-item scale was left with three factors accounting for 61.3% of the variance, with a decent KMO at .872. There was no sphericity ($\chi^2(105) = 684.9, p < .001$). The resulting 15-item scale had an alpha of .890. Factor alphas were as follows:

1. Factor 1, Satisfaction with Time Management Behaviors: alpha .897, 9 items
2. Factor 2, Track and Evaluate: alpha .755, 3 items
3. Factor 3, Set Intentions: alpha .700, 3 items

The final scale is in Figure E4.

Factor 1/Satisfaction with Time Use accounted for 28.9% of the variance. Factor 2/Track and Evaluate is composed of items from Macan’s Mechanics dimension, and accounted for 18.0% of the variance. Factor 3/Set Intentions is composed of items from Macan’s Goals dimension, and accounted for 13.9% of the variance. The final solution is in Table E1.
### Table E1

**Variables in Time Factors, in Order of Loading with Source Measures**

<table>
<thead>
<tr>
<th>Factor</th>
<th>Name</th>
<th>Prompt</th>
<th>Scale</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Satisfaction with Time Use</td>
<td>“This semester, how satisfied have you been with your ability to do _____”</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>1. Very dissatisfied</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>2. Dissatisfied</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>3. Neutral</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>4. Satisfied</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>5. Very satisfied</td>
</tr>
<tr>
<td></td>
<td>Variable</td>
<td>Source</td>
<td>Loading</td>
</tr>
<tr>
<td></td>
<td>Follow routines</td>
<td>SSTS</td>
<td>.648</td>
</tr>
<tr>
<td></td>
<td>Deal with the unexpected</td>
<td>SSTS</td>
<td>.676</td>
</tr>
<tr>
<td></td>
<td>Start tasks early</td>
<td>SSTS</td>
<td>.682</td>
</tr>
<tr>
<td></td>
<td>Track obligations</td>
<td>SSTS</td>
<td>.703</td>
</tr>
<tr>
<td></td>
<td>Plan ahead</td>
<td>SSTS</td>
<td>.727</td>
</tr>
<tr>
<td></td>
<td>Estimate task time</td>
<td>SSTS</td>
<td>.728</td>
</tr>
<tr>
<td></td>
<td>Follow through on tasks</td>
<td>SSTS</td>
<td>.827</td>
</tr>
<tr>
<td>2</td>
<td>Track and Evaluate</td>
<td>“For the questions below, please select the answer that best describes you as you have been this semester.”</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>1. Strongly disagree</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>2. Disagree</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>3. Neither agree nor disagree</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>4. Agree</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>5. Strongly agree</td>
</tr>
<tr>
<td></td>
<td>Variable</td>
<td>Source</td>
<td>Loading</td>
</tr>
<tr>
<td></td>
<td>Review daily activities</td>
<td>TMBS</td>
<td>.832</td>
</tr>
<tr>
<td></td>
<td>Keep a daily log</td>
<td>TMBS</td>
<td>.732</td>
</tr>
<tr>
<td></td>
<td>Evaluate schedule</td>
<td>TMBS</td>
<td>.695</td>
</tr>
<tr>
<td></td>
<td>Try to increase efficiency</td>
<td>TMBS</td>
<td>.628</td>
</tr>
<tr>
<td>3</td>
<td>Set Intentions</td>
<td>“For the questions below, please select the answer that best describes you as you have been this semester.”</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>1. Strongly disagree</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>2. Disagree</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>3. Neither agree nor disagree</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>4. Agree</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>5. Strongly agree</td>
</tr>
<tr>
<td></td>
<td>Variable</td>
<td>Source</td>
<td>Loading</td>
</tr>
<tr>
<td></td>
<td>Break down tasks</td>
<td>TMBS</td>
<td>.796</td>
</tr>
<tr>
<td></td>
<td>Set short-term goals</td>
<td>TMBS</td>
<td>.735</td>
</tr>
<tr>
<td></td>
<td>Set Daily Priorities</td>
<td>TMBS</td>
<td>.645</td>
</tr>
</tbody>
</table>
Analysis of Distribution Across Groups

The study sample was diverse in terms of age, race and other demographics, and unbalanced in terms of gender. All demographic groupings were examined for significant associations with time management factors and outcomes. For groups and the data overall, the multilevel nature of the data was a significant concern: students came from ten different courses, and there could be different relationships between outcome variables among these courses. However, given the low number of schools (level 2 variables), multilevel modeling was not appropriate (Maas & Hox, 2005).

**Nonparametric tests.** Independent sample Kruskal-Wallis and Mann-Whitney tests, as appropriate, were run for each group against the grade, course persistence and college wellbeing variables, as well as the combined outcome variable and the three factor variables developed for time management. Results that reached a $p$-value below .05 are noted in Table E2. However, dividing alpha .05 by number of variables (23), the Bonferroni correction yields a $p$-value threshold of .002. The only result that reached this threshold was dependent care based on age. As expected, older students had higher dependent care obligations, on average.
Table E2

*Group Differences in Variables: Summary of Significant p-values from Non-parametric Rank-order Tests (Mann-Whitney and Kruskal-Wallace), Before Bonferroni correction*

<table>
<thead>
<tr>
<th>Group</th>
<th>Factor</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age</td>
<td>TMBS</td>
<td>*</td>
</tr>
<tr>
<td></td>
<td>CSSWQ</td>
<td>*</td>
</tr>
<tr>
<td></td>
<td><strong>Dependent Care</strong></td>
<td>***</td>
</tr>
<tr>
<td></td>
<td>F3 Set Intentions</td>
<td>*</td>
</tr>
<tr>
<td></td>
<td>Short-Term Goals</td>
<td>*</td>
</tr>
<tr>
<td></td>
<td>Study Well</td>
<td>*</td>
</tr>
<tr>
<td></td>
<td>Grateful to People Who Helped</td>
<td>*</td>
</tr>
<tr>
<td></td>
<td>TMBS Goals</td>
<td>*</td>
</tr>
<tr>
<td></td>
<td>CSSWQ</td>
<td>*</td>
</tr>
<tr>
<td>Gender</td>
<td>Overwhelm</td>
<td>*</td>
</tr>
<tr>
<td>Course Background</td>
<td>F3 Set Intentions</td>
<td>**</td>
</tr>
<tr>
<td></td>
<td>Dependent Care</td>
<td>*</td>
</tr>
<tr>
<td>1st Gen or Not</td>
<td>Students Here Like Me as I Am</td>
<td>**</td>
</tr>
<tr>
<td>Prior GPA</td>
<td>Combined Success</td>
<td>**</td>
</tr>
<tr>
<td></td>
<td>Feel in Control of Time</td>
<td>*</td>
</tr>
<tr>
<td>Enrolled in a Degree Program</td>
<td>Study from 1 to 4 am</td>
<td>*</td>
</tr>
<tr>
<td></td>
<td>Reminder Notes</td>
<td>*</td>
</tr>
<tr>
<td></td>
<td>Short-Term Goals</td>
<td>*</td>
</tr>
<tr>
<td></td>
<td>Underestimate Time</td>
<td>*</td>
</tr>
<tr>
<td></td>
<td>Course Load</td>
<td>**</td>
</tr>
<tr>
<td></td>
<td>F3 Set Intentions</td>
<td>**</td>
</tr>
<tr>
<td></td>
<td>Gratitude</td>
<td>*</td>
</tr>
<tr>
<td></td>
<td>Care for Dependents</td>
<td>*</td>
</tr>
</tbody>
</table>

\[ p < .05. \quad ** p < .01. \quad *** p < .001 \]

*Note: After correction for family-wise error, only Dependent Care by Age was significant.*
Correlations. Bivariate correlations revealed several significant relationships, summarized in Table E3. Study times of day had significant associations with course outcome. Spending more time on the course site from midnight to four or six am was positively associated with degree status and taking the course fully online ($p < .01$). Continuing-generation students were more likely to study from five to nine am, and to get more sleep ($p < .01$). Surprisingly, studying between six am and noon was negatively associated with course outcome, but positively associated with good grades ($p < .01$), while studying between six pm and midnight was associated with lower grades ($p < .01$). Also surprising was a strong negative association between number of time management tools used and course outcome ($p < .001$). More leisure time online was unexpectedly associated with more sleep ($p < .01$). After Bonferroni correction for family-wise error, the only association that was still significant was that between time management tool use and course completion: those students who used four or more time management tools were less likely to complete the course than those who used three or less. This makes sense when a “keep it simple” philosophy is applied: more than three tools may be too much of a good thing.

As to first-generation status, students for whom at least one parent or guardian had not attended college got less sleep ($p = .006$) and worked more hours for pay ($p = .001$). While the sleep relationship is not significant after Bonferroni correction (alpha = .002), it was close ($p = .006$), and worth noting. The relationships were slightly weaker for fully first-gen students (neither parent or guardian attended college), but the figure for work week hours was still notable ($p = .006$). There was no correlation between first-gen status and grades or course completion.
Table E3

*Pearson Correlations Between Study Times, Sleep, Number of Tools, and Track & Monitor, and Demographic Factors with p-values < .05 Before Bonferroni Correction*

<table>
<thead>
<tr>
<th></th>
<th>12 to 6 am</th>
<th>1 to 4 am</th>
<th>5 to 9 am</th>
<th>6 am to noon</th>
<th>6 pm to 12 am</th>
<th>Hours of Sleep</th>
<th># of Time Tools</th>
<th>Track &amp; Monitor</th>
</tr>
</thead>
<tbody>
<tr>
<td>Course outcome</td>
<td>-.248*</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>-.344**</td>
</tr>
<tr>
<td>Grade</td>
<td>.226*</td>
<td>-.288*</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Not 1st Gen</td>
<td>.220*</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>.263*</td>
</tr>
<tr>
<td>Degree status</td>
<td>.222*</td>
<td>.253*</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Course load</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Fully online</td>
<td>.247*</td>
<td>.263*</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Dependent Care</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>.312**</td>
</tr>
<tr>
<td>Work Hours</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>-.345**</td>
<td></td>
</tr>
<tr>
<td>Leisure Time</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>.220*</td>
</tr>
</tbody>
</table>

*p < .05. **p < .01. ***p < .001
Note: After correction for family-wise error, a significant relationship (p = .002) still existed between course completion and number of time management tools used
Appendix F. Demographic Differences Between First- and Continuing-Gen Students

Table F1

*Key Differences Between First- and Continuing-Gen Study Participants*

<table>
<thead>
<tr>
<th>Independent Variables – Percentage (n)</th>
<th>Get at least 7 hours’ sleep</th>
<th>Work at least 45 hours a week</th>
<th>Do not work at all</th>
<th>Care for dependents 45 or more hours a week</th>
<th>Do not care for any dependents</th>
<th>Report having less background in course subject than peers</th>
<th>Female</th>
<th>Age less than 28</th>
<th>Age 33 or older</th>
</tr>
</thead>
<tbody>
<tr>
<td>First Gen</td>
<td>50.0</td>
<td>41.9</td>
<td>9.7</td>
<td>18.8</td>
<td>28.1</td>
<td>45.0</td>
<td>80.0</td>
<td>17.5</td>
<td>65.0</td>
</tr>
<tr>
<td></td>
<td>(40)</td>
<td>(32)</td>
<td>(32)</td>
<td>(32)</td>
<td>(32)</td>
<td>(40)</td>
<td>(40)</td>
<td>(40)</td>
<td>(40)</td>
</tr>
<tr>
<td>Continuing Gen</td>
<td>67.6</td>
<td>18.9</td>
<td>24.5</td>
<td>11.1</td>
<td>44.4</td>
<td>32.3</td>
<td>69.1</td>
<td>38.2</td>
<td>41.2</td>
</tr>
<tr>
<td></td>
<td>(68)</td>
<td>(53)</td>
<td>(53)</td>
<td>(53)</td>
<td>(53)</td>
<td>(68)</td>
<td>(68)</td>
<td>(68)</td>
<td>(68)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Independent Variables – Means</th>
<th>Hrs of sleep</th>
<th>Hours of work</th>
<th>Hours caring for dependents</th>
<th>Final grade</th>
</tr>
</thead>
<tbody>
<tr>
<td>First Gen</td>
<td>6.7</td>
<td>38.0</td>
<td>14.7</td>
<td>3.65</td>
</tr>
<tr>
<td></td>
<td>(40)</td>
<td>(32)</td>
<td>(32)</td>
<td>(28)</td>
</tr>
<tr>
<td>Continuing Gen</td>
<td>7.0</td>
<td>24.9</td>
<td>12.6</td>
<td>3.72</td>
</tr>
<tr>
<td></td>
<td>(68)</td>
<td>(53)</td>
<td>(53)</td>
<td>(51)</td>
</tr>
</tbody>
</table>
Table F2

*Differences (p < 0.10)* in Mean Age, Hours of Work, and Study Times, Between First-Gen and Continuing-Gen Study Participants

<table>
<thead>
<tr>
<th>Variable</th>
<th>1st Gen Mean (n)</th>
<th>Non 1st Gen Mean (n)</th>
<th>Mean difference (CI)</th>
<th>t value (df)</th>
<th>p value</th>
<th>Sig. level (2-tailed)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hours sleep per night</td>
<td>6.7 hours (40)</td>
<td>7.0 hours (68)</td>
<td>-.43 (-.92, .07)</td>
<td>-1.706 (106)</td>
<td>.091</td>
<td>&lt; .10</td>
</tr>
<tr>
<td>At least 7 hours sleep?</td>
<td>75% (40)</td>
<td>84% (68)</td>
<td>-.09 (.05, -.02)</td>
<td>-1.794 (106)</td>
<td>.070&lt; .10</td>
<td></td>
</tr>
<tr>
<td>Morning study (% access 5 to 9 am)</td>
<td>12.3% (38)</td>
<td>16.5% (60)</td>
<td>-4.16 (2.10, -8.32)</td>
<td>-2.181 (95)</td>
<td>.032&lt; .05</td>
<td></td>
</tr>
<tr>
<td>Hours work per week</td>
<td>38.0 hours (31)</td>
<td>25.0 hours (53)</td>
<td>13.03 (3.76, 22.30)</td>
<td>2.797 (82)</td>
<td>.006 &lt; .01</td>
<td></td>
</tr>
<tr>
<td>Agec</td>
<td>3.4 (40)</td>
<td>2.9 (68)</td>
<td>.50 (.21, .09)</td>
<td>2.414 (106)</td>
<td>.017 &lt; .05</td>
<td></td>
</tr>
</tbody>
</table>

a. Only differences to alpha 0.10 are reported in this table.
b. Levene’s test result was over p = .05, so equal variances are not assumed.
c. Age was on an ordinal scale, from (1) 18 to 22 years old, to (4) = 33 or older.
Figure F1. Bar Chart Comparison of Hours Worked for First- and Continuing-Gen

Comparison of work hours between first- (n=32, blue) and continuing- (n=53, red) gen students
Figure F2. Bar Chart Comparison of Ages of First- and Continuing-Gen

First-generation (blue) $n = 40$, continuing-generation (red) $n = 68$. 