USING A SELF-MANAGEMENT PROJECT TO IMPROVE STUDENT PERFORMANCE IN AN ONLINE INTRODUCTORY STATISTICS COURSE

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ABSTRACT

USING A SELF-MANAGEMENT PROJECT TO IMPROVE STUDENT PERFORMANCE IN AN ONLINE INTRODUCTORY STATISTICS COURSE

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The primary purpose of this study was to examine the effects of a self-management project on student performance in an online introductory statistics course. Two classes were compared: students in one class set daily goals for their study behavior and monitored this behavior; the other class set daily goals for their study behavior, monitored this behavior, *and* arranged self-delivered consequences for meeting their goals. Statistics anxiety, self-regulation, self-management skills, motivation, technology use, and digital literacy variables were measured to help compare the two classes on pre-existing characteristics. A secondary purpose of the study was to examine the effects of using participation points as an incentive for posting questions to an online discussion board using a within-class ABA design. The class with the self-management project performed significantly better on quizzes and exams. Thus, the project appeared to improve student performance. Providing participation points for posting questions increased the number of questions posted, and the number of questions decreased significantly when the incentive was removed. Limitations and future direction are discussed.

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Introduction

Since the early 1990s, the number of students enrolling in US colleges and universities has steadily increased. According to the US Department of Education, during the periods of 1992 to 2002 and 2002 to 2012 the number of college students enrolled grew by 15% and 24%, respectively (http://nces.ed.gov/fastfacts/display.asp?id=98). As of 2013, US colleges and universities enrolled 17.5 million undergraduates and 2.9 million graduate students (http://nces.ed.gov/programs/coe/indicator_csb.asp). In 2013, US postsecondary institutions awarded over 750,000 Bachelor's degrees in areas that often require some sort of statistics course, including biological and biomedical sciences, business, health sciences, and psychology (http://nces.ed.gov/programs/digest/d14/tables/dt14_322.10.asp). Completion of a statistics course is not only required for graduation for some majors, but introductory statistics courses may also fulfill general education requirements and/or serve as prerequisites for many upper-level courses. For example, at San José State University (SJSU), students can earn credit toward their general education requirements by passing an introductory statistics course (STAT 95 *Elementary Statistics* in Area B4), and the introductory statistics course is a prerequisite for several upper-division courses in the Psychology major.

Despite the importance of statistics courses for earning a college degree, a sizable number of students do not pass their statistics courses. For instance, Lunsford and Poplin (2011) reported that nearly 40% of their students did not pass their introductory statistics course. Cook (2010) reported failure rates between 15% and 41% for an introductory statistics course in an economics department. At SJSU, between the years of 2006 and 2012, 26% of students in the Department of Psychology earned a C- or lower in the elementary statistics course (http://www.iea.sjsu.edu/Courses/prefixes.cfm?version=graphic&CRS=STAT&CRSDESC=Statistics). Thus, statistics courses prevent some students from moving through their degree programs in a timely manner, increasing the costs of education and delaying graduation.

Some researchers have identified students' lack of basic math skills as one potential reason for these relatively high failure rates (e.g., Johnson & Keunnen, 2006; Lunsford & Poplin, 2011). In addition, researchers have identified other barriers to student success in statistics courses, including statistics anxiety, lack of motivation and self-efficacy, and poor self-regulation skills while enrolled in college statistics courses (e.g., Onwuegbuzie & Daley, 1999; Onwuegbuzie & Wilson, 2003; Onwuegbuzie, 2004). To mitigate the problem of poor preparation in mathematics, some postsecondary institutions require students to complete prerequisites in mathematics before taking introductory statistics courses. For example, SJSU requires two years of high school algebra and a passing score on the Entry Level Mathematics (ELM) examination prior to taking STAT 95 (http://info.sjsu.edu/web-dbgen/catalog/courses/STAT095.html). Because the target students in the current study were enrolled in STAT 95, we did not focus on basic math skills as a means of improving student success. Instead, we focused on ways to help students improve their self-regulation skills and motivation to work on the course-related activities.

Statistics Anxiety

Statistics anxiety has become a growing concern among researchers seeking to improve statistics education. According to Onwuegbuzie and Wilson (2003), an estimated 80% of graduate students experience a high degree of statistics anxiety. In general, statistics anxiety can be defined as a multi-dimensional construct in which the person experiences a strong negative emotional reaction when confronted with any form of statistics (Onwuegbuzie, 2004; Onwuegbuzie & Daley, 1999; Onwuegbuzie & Wilson, 2003). Cruise, Cash, and Bolton (1985) examined the multidimensionality of statistics anxiety and identified six components of this construct: (a) worth of statistics, (b) interpretation anxiety, (c) test and class anxiety, (d) computational self-concept, (e) fear of asking for help, and (f) fear of statistics teachers.

Worth of statistics refers to the extent to which students feel that statistical concepts are worthy studying for a variety of reasons, including their personality or the usefulness of these concepts. *Interpretation anxiety* involves discomfort resulting from making decisions about statistical results. *Test and class anxiety* results from working on class assignments, taking exams, and attending class. *Computational self-concept* involves anxiety resulting from students' poor view of their own math skills and background. *Fear of asking for help* refers to anxiety evoked by the thought of seeking assistance to solve statistical problems or understand statistical concepts. *Fear of statistics teachers* results from students' conceptions of the characteristics of statistics instructors. Cruise et al. (1985) developed the Statistics Anxiety Rating Scale (STARS) to assess these six dimensions of statistics anxiety. Higher scores on each subscale indicate higher levels of anxiety. Previous research has found that test and class anxiety are the most statistically significant components of the STARS (Onwuegbuzie & Wilson, 2003). The STARS is one of the most popular questionnaires for assessing statistics anxiety and is described in more detail in the Method section.

Some symptoms of statistics anxiety include negative anticipation, fear, panic, and worry as a result of taking statistics courses (Onwuegbuzie, 2004). Symptoms of statistics anxiety are often situation-specific in which the symptoms are only experienced when the student is applying statistical concepts and/or learning about statistics (Onwuegbuzie, 2004). Statistics anxiety has also been found to occur for students enrolled in research methodology courses, which often incorporate statistical concepts (Onwuegbuzie & Daley, 1999). In a comprehensive literature review on statistics anxiety, Onwuegbuzie and Wilson (2003) noted that statistics anxiety involves *situational*, *dispositional*, and *environmental* antecedents prior to entry into statistics courses. These elements can serve as predictors of statistics anxiety.

Situational antecedents are factors surrounding the student's overall success and understanding in statistics courses. Some examples include students' familiarity and attitude towards their status in the course, prior knowledge in mathematics and statistics, and overall interest in statistics education (Onwuegbuzie & Wilson, 2003). Although the initial attitudes students have toward statistics may be uncontrollable, there may be ways to change their attitudes in the course as the semester progresses through motivational and engagement techniques. Schacht and Steward (1990) suggested using teaching gimmicks (e.g., allowing students to create real life application of statistics examples) and incorporating humor to reduce anxiety in the classroom.

Dispositional antecedents are factors that students bring with them to a statistics course. For example, some students come to the class equipped with higher levels of intellectual ability and/or motivation, a more thorough understanding of mathematics, and better self-management skills in a classroom compared to their peers (Onwuegbuzie & Wilson, 2003). Some students, however, lack understanding or interest in mathematics, have poor self-management skills, and procrastinate with respect to reading and completing homework. Indeed, procrastination is quite common in college students with prevalence rate estimated at approximately 95% (Onwuegbuzie, 2004), and researchers have begun to focus on its effects in the classroom. The majority of research on procrastination shows that students who procrastinate show decreased academic achievement (Onwuegbuzie, 2004) and psychological disturbances and distress (Walsh & Ugumba-Agwunobi, 2002). Dispositional factors are also related to self-esteem, and low self-esteem may contribute to statistics anxiety (Zeidner, 1991). Although it is difficult to control dispositional antecedents prior to course entry, these factors serve as predictors of success and anxiety levels in statistics and may be changed during a course, for example, by teaching students time-management skills.

Environmental antecedents are factors related to past events and demographic variables such as gender, race/ethnicity, and age. Research on statistics anxiety involving environmental factors have found that females tend to show higher levels of statistics anxiety than do males (Onwuegbuzie & Wilson, 2003) and that African-American students show higher levels of statistics anxiety than do White students (Onwuegbuzie, 1999). The literature on environmental antecedents suggest that increased statistics anxiety for these groups results from the overall pressure from their environment to do well early on in their school careers and from a fear of underachievement in higher education (Onwuegbuzie & Wilson, 2003).

As noted by Onwuegbuzie and Wilson (2003), dispositional antecedents of statistics anxiety include students' individual differences. Some researchers have begun to investigate personality traits such as academic procrastination, perfectionism, and trait anxiety in the classroom as correlates of statistics anxiety (e.g., Onwuegbuzie & Daley, 1999; Onwuegbuzie, 2004; Walsh & Ugumba-Agwunobi, 2002). Onwuegbuzie and Daley (1999) investigated the relationship between perfectionism and statistics anxiety. These authors defined perfectionism as "the tendency to set and pursue unrealistic goals across different domains" (p. 1089). In their study, 107 students enrolled in a graduate-level research method course completed the Multidimensional Perfectionism Scale (MPS) and the STARS. The MPS is divided up into three subscales (i.e., *self-oriented perfectionism*, *other-oriented perfectionism*, and *socially prescribed perfectionism*). *Self-oriented perfectionism* is defined as setting unrealistic goals and high standards in order to maintain a sense of self-worth and avoid failure. *Other-oriented perfectionism* is defined as setting unrealistic goals and high standards for other people. Other-oriented perfectionists thoroughly monitor and evaluate others' behaviors. *Socially prescribed perfectionism* is defined as believing that others hold unrealistic goals and standards and evaluate the individual's behavior. Socially prescribed perfectionists feel the pressure from other people to avoid failure and to be "perfect." In this context, "others" refers to friends, family, professors and classmates, as well as anyone else the individual feels is in a position to judge him or her and/or pressure the individual to perform at a high standard. Scores on the MPS tended to predict different levels of statistics anxiety. More specifically, those students who showed higher levels of other-oriented and socially prescribed perfectionism tended to show higher levels of statistics anxiety. Interestingly, Onwuegbuzie and Daley found evidence of a moderately low positive relationship between socially prescribed perfectionism and both the *fear of asking for help* component and the *interpretation anxiety* component on the STARS. They suggested that the link between these two components may be due to the student having a fear of embarrassment associated with socially derived expectations. These authors also suggested that statistics anxiety may derive from students' feeling of helplessness in the classroom when unrealistic standards are expected from their instructor and peers (i.e., socially derived expectations). In the current study, one of our goals was to make the learning environment more approachable while still holding strong expectations in academic achievement for the students.

Onwuegbuzie (2004) investigated the relationship between academic procrastination and statistics anxiety. In this study, 135 graduate students enrolled in a research methods course completed the Procrastination Assessment Scale-Students (PASS) and the STARS. The PASS is an assessment that asks participants to rate different tasks on a 1 to 5 scale based on the frequency of procrastination they experience when asked to complete the task and how difficult it is to complete the task. Between

40% and 60% of graduate students reported that they procrastinate when writing a term paper, studying for exams, or completing reading assignments. Interestingly, 65% to 75% of students wanted to decrease or stop their procrastination. Although Onwuegbuzie (2004) found a positive relationship between statistics anxiety and academic procrastination, there is no clear evidence that this relationship is causal in nature, nor can we be sure of the directionality of the relationship. Onwuegbuzie suggested that the relationship may be bidirectional, such that students who enter a course as academic procrastinators quickly evaluate the importance and difficulty/amount of work required and thereby develop a sense of anxiety towards statistics. This anxiety then leads to increased procrastination as students learn to avoid the statistical material and the anxiety it produces. He also found that the rate of academic procrastination tends to increase as course difficulty and complexity increases. Furthermore, he suggested that, although some students may show lower levels of procrastination in undergraduate education, once they are admitted to graduate school their level of procrastination tends to increase. However, he postulated that graduate students may procrastinate for different reasons than do undergraduates; for example, graduate students tend to be more self-perfectionists and have a greater need to impress others in their work. The most important and interesting findings from this study that relate to the present study is that there is a positive correlation between procrastination and specific types of anxiety found among students enrolled in statistics and research methodology course (i.e., *fear of failure*, *test anxiety*, *social anxiety*, and *self-consciousness*). In our study, we viewed procrastination as a behavioral habit that could be changed rather than an enduring personality trait.

Therefore, we implemented an intervention that involved setting clear academic goals and incentivizing meeting those goals using self-management techniques (Malott & Harrison, 2006) in an attempt to reduce students' procrastination.

Another personality factor that has been examined in the research on statistics anxiety is trait anxiety, which is a consistent and enduring tendency to feel anxious. People with higher levels of trait anxiety often respond to ambiguous stimuli as being more threatening compared to people with lower levels (Walsh & Ugumba-Agwunobi, 2002). Walsh and Ugumba-Agwunobi (2002) expanded on the findings in Onwuegbuzie and Daley (1999) by examining the relationship between statistics anxiety and the personality traits of perfectionism, procrastination, and trait anxiety. They recruited 93 undergraduate students enrolled in a statistics/research methodology course and administered the MPS, the STARS, the State/Trait Anxiety Inventory (STAI) to assess trait anxiety, and the Aitken's Procrastination Inventory (API) to assess procrastination. Interestingly, these authors found a significant positive correlation between self-oriented perfectionism and computational self-concept (i.e., perception of one's ability in statistics and math). In contrast to these results, Onwuegbuzie and Daley (1999) did not find a significant relationship between these two constructs. However, Walsh and Ugumba-Agwunobi (2002) suggested that the relationship they found between self-oriented perfectionism and computational self-concept may be due to one's individual history of taking statistics courses and performance on statistics tests. These authors noted that previous research has shown that past failure is a key aspect of self-oriented perfectionism such that individuals with this type of perfectionism will focus on their weaknesses with respect to statistical concepts, which results in higher levels of procrastination. Simply put, their perfectionism causes them to evaluate their statistical abilities negatively and this leads to procrastination. Furthermore, focusing on past failures may contribute to the development of trait anxiety that affects other aspects of life outside of academic achievement. Walsh and Ugumba-Agwunobi (2002) also found that highly anxious individuals showed increased levels of fear of asking for help with statistical concepts. The authors proposed that this relationship is due to the fact that anxious individuals may anticipate a threat to their self-concept by demonstrating that they do not understanding the subject in asking for help. Anxious students may also fear asking for help because they have had their questions disregarded or ridiculed in past academic settings. In our current study, we confronted this problem by trying to develop an engaging learning environment that treated all student questions as meaningful and important. Whenever a student asked a question, we attended to it as soon as possible and made it clear to the student the question was a good one worth asking. Student questions were never met with disdain or ignored. We also provided points for asking questions to incentivize this behavior.

Online Learning

The statistics course that is the focus of the present study was delivered entirely online. Many colleges and universities are increasingly utilizing customized online courses or incorporating material from Massive Open Online Courses (MOOC). There are a variety of reasons for doing so, including shifting student demographics, increased demand for continuing education, and limited classroom space and course offerings.

Online courses are typically designed and administered through a web-based platform (e.g., Udacity, Coursera) or learning management systems (LMS; e.g., Canvas, Desire2Learn, Blackboard). In fully online courses, materials, assignments, quizzes, and exams are available online, and students do not meet in person. All contact between the students and instructor/TAs is carried out through the online platform. Online learning can be seen as both beneficial and problematic compared to traditional in-person ("face-to-face") courses. However, online courses are becoming increasingly prevalent. The number of US college students taking an online course at degree-granting postsecondary institutions increased from 1.6 million in 2002 to 6.7 million in 2011 (Allen & Seaman, 2013). Therefore, the features of online classes and characteristics of students in those classes that contribute to successful student learning outcomes will become increasingly important areas for research.

In our study, the online statistics courses (STAT 95) used materials developed for Udacity by two SJSU Department of Psychology faculty members (Dr. Ronald Rogers and Dr. Sean Laraway). Although our study did not investigate a true MOOC, data on MOOCs can provide valuable guidance when designing online classes. The STAT 95 classes examined in this study used the same lecture videos and problem sets available on Udacity's learning platform. One benefit to online courses, such as our online course and other MOOC courses, is that they can enroll more students than can face-to-face courses. It is important to note that, most MOOC courses are free of charge and are completely open to the public, while online courses affiliated with a university and degree program have tuition costs and may require students to be admitted into the university before enrolling. While fully open MOOC courses may be found to have relatively low completion rates, it is more often found that online courses affiliated with universities have higher completion rates due to degree requirement and motivation to complete the course. Jordan (2014) investigated the factors affecting enrollment rates and completion in free MOOC courses offered at Coursera, EdX, and Udacity. Jordan found that total enrollment rates in MOOC courses range from 4,500 to 226,652 students, and, as time progressed, enrollment participation decreased significantly. Furthermore, Jordan found that the average completion rate was roughly 5%, and there was a negative relationship between the completion rate and course length. Although completion rates are found to be less than 10%, with a MOOC course enrollment total of 50,000+ students, a large amount of students still complete and benefit from the course. In addition, not all students need to finish the entire course to benefit from that course; they may only need parts of the course to fulfill their interests and/or goals for enrolling in the course in the first place.

Online courses, including MOOCs, vary in their design, organization, and pedagogy. One pedagogy that has been systematically investigated is a variation on Keller's (1968) personalized system of instruction or PSI (Pear et al., 2011). PSI was originally developed as an alternate teaching method compared to the traditional lecture-based style of teaching. PSI allows students to work at their own paces and develop a mastery of earlier material before moving on to later material (Pear et al., 2011). Although PSI was originally developed for in-person classes, the PSI method was later adapted to online classes by Joseph Pear and colleagues at the University of Manitoba.

For example, Pear and Kinsner (1988) developed the computer-aided personalized system of instruction (CAPSI), which uses computer-based programs to enhance learning among college students. Instructors administer all of the material, including lectures (in the form of video and/or written text), assignments, quizzes, and exams through their learning platform (Pear & Novak, 1996; Pear, 2003). As in many other online courses, students in CAPSI courses could access lecture material and assignments at any location and time. Students work at their own paces and their correct responses on assignments are immediately reinforced via feedback (Pear et al., 2011). CAPSI and other online courses allow universities to enroll more students and hold multiple sections compared to traditional face-to-face course (Pear, 2003). Generally, these courses require one instructor and a few teaching assistants (TAs) to help provide feedback on student work (Pear, 2003). Instructors and TAs can work with each student individually rather than as a group through a communication platform (e.g., email, Skype, discussion boards, online chat rooms). We adapted some aspects of the CAPSI system to our course. For example, we allowed students to work at their own paces, although all relevant material had to be completed prior to each scheduled exam. One difference is that students in our course did not get immediate feedback on their quiz or exam answers.

Another element of CAPSI that we adapted for our study was the use of peer reviewers. During the duration of the CAPSI course, students are assigned to peer review other students' course work and provide meaningful feedback, and they earn assignment points for doing so (Pear, 2003). Research on CAPSI shows that as the courses progress, peer reviewers tend to give more meaningful feedback, which shows that they get better with practice and gain mastery over the course material (Pear, 2003). Peer reviewers along with the instructor and TAs allow the students to gain rapid feedback on their work (Pear and Novak, 1996). In our study, students were awarded points for answering other students' questions and commenting on discussion board postings. They could also earn points for posting their own questions regarding course material (but not logistical questions such as those about due dates). This was done because in previous classes, few students posted questions on the course discussion boards (S. Laraway, personal communication). Through a discussion board application (Piazza) running on the Canvas LMS students could ask and answer questions at any time during the course. The application was available 24 hours a day, seven days a week. Like CAPSI, this allowed students to get rapid and meaningful feedback to their questions. Unlike CAPSI, the peer-review system was not as well structured in our course.

Academic Procrastination

One of the main concerns we have with the growing popularity of online courses is the effect of academic procrastination on course performance. Online courses require that students have good self-discipline and self-regulation habits in order to do well. Students enrolled in online courses have a much stronger responsibility to decide when and where they are going to complete the coursework than a traditional face-to-face course. Students enrolled in online courses may be predisposed to a higher chance of engaging in academic procrastination due to situational antecedents as described by Onwuegbuzie and Wilson (2003). As discussed previously, Alexander and Onwuegbuzie (2006) proposed that academic procrastination is a coping strategy that students use to deal with academic stress. These authors investigated the role of hope and optimism in academic procrastination as a healthy coping strategy. Alexander and Onwuegbuzie suggested that students who engage in maladaptive procrastination as a way to cope with academic procrastination never learned more adaptive strategies for coping with academic stress. Hope as a coping strategy is defined as being self-aware of the important pathways we must take reach our goals and the perceived capability of completing those goals while staying motivated (Snyder, 2002). Alexander and Onwuegbuzie found that lower levels of hope were correlated with higher levels of anxiety and procrastination. It is important for researchers to identify ways to combat harmful predispositions in college students in the early phases of college courses. Alexander and Onwuegbuzie suggested that future research should investigate the role of hope and its potential to mitigate academic procrastination.

One of the clearest findings from the research on academic procrastination is the moderately strong negative correlation it has with academic performance (Moon & Illingworth, 2005). Although academic procrastination can be viewed as a behavior, some researchers view it as an enduring personality trait (e.g., Johnson & Bloom, 1995; Lee, Kelly, & Edwards, 2006; Steel, Brothen, & Wambach, 2001). A problem with this view is that it implies that academic procrastination is inflexible and cannot be changed. Therefore, students who have this trait have little hope for developing better self-regulation. In a longitudinal study, Moon and Illingworth (2005) investigated the debate to see how and if procrastination changes over time. Using latent growth curve modeling, these authors found that academic procrastination within a single semester had a curvilinear trend over time. They found that at the start of the semester most students would study and complete assignments in a timely manner, whereas in the middle of the semester the degree of procrastination was relatively higher than at the start of the semester. Finally, they found that as the semester came to an end, the degree of procrastination decreased. Moon and Illingworth argued that if academic procrastination was completely trait-based, then the amount of procrastination throughout a semester should be relatively stable. They provided evidence against the view that academic procrastination as a personality trait and suggested that future research compare trait theories with behavioral theories in the domain of procrastination. In the present study, we took the view that academic procrastination is partly a behavioral response (i.e., a coping strategy) to statistics anxiety, a bad habit that is common among college students, and a result of the lack of structure imposed on students' time by online classes. In taking this view, we then sought to reduce procrastination by having students develop and follow a self-management plan that incorporated explicit time-management strategies.

Research in personality psychology and both the Five-Factor Model and Three-Factor Model of Personality shows strong evidence of the association between procrastination and both neuroticism and conscientiousness (Johnson & Bloom, 1995; Lee et al., 2005; Steel et al., 2001). Neuroticism is associated with negative emotions such as anxiety, depression, and feelings of fear, worry, and low self-esteem (Johnson & Bloom, 1995; Lee et al., 2005). Conscientiousness is associated with goal-oriented behavior, motivation, and self-regulated behavior (Lee et al., 2005). Correlational research in personality and procrastination suggests that neuroticism has a curvilinear relationship with procrastination such that individuals who score moderately high on neuroticism tend to have higher levels of procrastination. In contrast, those who score severely high on neuroticism tend to have lower levels of procrastination (Johnson & Bloom, 1995). Johnson and Bloom suggested that the curvilinear relationship is due to neuroticism acting as an inhibiting factor when individuals express higher than normal levels of stress/neuroticism. For example, someone that has moderate feelings of worry about an upcoming assignment is more likely to procrastinate than someone that has extreme feelings of worry. The extreme feelings of worry cause the individual to attend to the threat sooner rather than later. Researchers have argued that neurotic behavior, being characterized by feelings of anxiety, enables threat avoidance behavior such as procrastination (Lee et al., 2005). Neurotic individuals see the assignment deadline as an imminent threat and therefore avoid it as long as possible. In contrast, conscientiousness has been found to have an inverse relationship with procrastination where individuals that score high on conscientiousness show low levels of procrastination (Lee et al., 2005). This finding is further strengthened by the relationship between neuroticism and conscientiousness, which has been also found to be an inverse relationship. However, when looking at specifically trait procrastination, researchers argue that behaviors related to neuroticism (e.g., delayed decision making due to imminent threats) predict behaviors related to conscientiousness (e.g., poor self-regulation and lack of goal-oriented behaviors) rather than conscientiousness predicting neuroticism (Lee et al., 2005). Furthermore, there is also debate on whether conscientiousness and procrastination are truly individual constructs despite the findings that there is a strong inverse relationship between the two as described by Lee et al. Both constructs are clearly related to subcategories (e.g., self-regulation, self-monitoring, self-efficacy) of the overall conscientiousness domain.

Self-Regulation

One of the main skills that students in online classes need is self-regulation, which involves self-monitoring, goal setting, proactive planning, and self-reflection (Zimmerman, 1998). Zimmerman (1990), in an overview of the research on self-regulated learning and academic achievement, defined self-regulated learners as individuals who proactively take the necessary steps in order to not only understand pieces of information but also develop a sense of mastery within the domain and subject. Self-regulated learners are in control of their own academic achievement and go through their education in a very systematic format in which they maintain high levels of self-motivation and critical analyses of class concepts and their own behavior. Self-regulated learners have an internal tendency to strive academically and maintain a high sense of motivation when it comes to learning; for example, they will continue to engage proactively in extra learning activities just to get a better sense of understanding in the subject. They also have a high sense of self-efficacy and understanding of their own strengths and weaknesses (Zimmerman, 1990). The self-regulated student may engage in extra practice sessions or ask more in-depth questions about concepts than do other students. Self-regulated learners also engage in metacognitive processes that involve planning, setting goals, organizing materials, self-monitoring, and self-evaluating their learning processes.

In the current study, one of our goals was to develop a program in which the students were required to do just this. Students were assigned a self-management project that required them to plan out their entire semester, set daily or weekly academic goals, and monitor and self-evaluate their academic behavior and performance. Zimmerman (1990) also noted that an important feature of self-regulated learning is a "self-oriented feedback" loop. This feedback loop is a process that self-regulated learners use to better understand their learning strategies and to make adjustments where they see fit. Our study arranged for students to develop a self-oriented feedback loop by having them reflect on their performance and make adjustments throughout the semester. They then had to report on their self-reflection and describe any changes to their academic behavior they devised based on this self-reflection. A bulk of the research presented in Zimmerman (1990) identified the ability to self-evaluate one's own performance and make changes based on that perception as the main aspect responsible for becoming a self-regulated learner. With the use of an online learning platform and the ability to give rapid feedback to our students, we attempted to help students become better self-regulated learners through these means. Our goal was to help students clearly understand their own specific learning processes and steps required to learn in a style that is unique to themselves.

Zimmerman (2008) reviewed the current literature on self-regulated learning and motivation and noted that computer-assisted environments could be useful for providing interventions for improving student self-regulation skills and motivation. Zimmerman pointed out that online software allows students access to multiple social sources (e.g., instructor, teaching assistants, and peers). We incorporated the third-party discussion board application Piazza to help students communicate with multiple social sources (the instructor, TAs, and other students). Using Piazza, students were able to keep track of the questions asked throughout the semester, so that they could return to previous topics/discussions if needed. Lastly, in Zimmerman's review, it was noted that using diary measures and time-series data, students can set goals, monitor those goals, and make changes as they progress through the semester (self-regulated learning behavior). Furthermore, students can use the diaries to help make adjustments to their time-management when working through the course. In an online course, time management is crucial for success. In the current study, we utilized a self-management project as a way for students to keep track of their progress in the course similar to the diaries/time series data entries described in Zimmerman, 2008.

Self-efficacy is also a very important aspect of self-regulated learning. Academic self-efficacy can be defined as the confidence students have about their own learning behavior and performance (Cho & Shen, 2013). Previous research has shown that self-efficacy is positively correlated with both self-regulation and academic performance (Cho & Shen, 2013). Self-efficacy is also related to goal orientation, which is the student's internal tendency to set and complete goals while engaging in diverse learning activities (Cho & Shen, 2013). Goal orientation can be divided up into two types: intrinsic and extrinsic. These two types are derived from the work of Pintrich (1999). Intrinsic goal orientation is the internal tendency to set goals that relate to developing mastery within the subject for the sake of learning. Extrinsic goal orientation is the tendency to set goals that results in obtaining good grades in the course. Intrinsic goal orientation is positively related to self-regulation and academic performance. In contrast, extrinsic goal orientation is not related to self-regulated learning, nor does it have any direct influence on student academic achievement (Cho & Shen, 2013).

Cho and Shen suggested that online learning environments should use problem-based learning to enhance student intrinsic goal orientation. They proposed that problem-based learning allows students to relate the subject to real-life situations, which helps students engage in in-depth learning and intrinsic goal formation. Becoming more intrinsically motivated will help students to become more goal oriented and show higher levels of success (Cho & Shen, 2013). Luckily, with introductory statistics courses, it should be fairly easy for instructors to apply the topic to real world situations. In our study, we were able to apply statistical concepts to real world issues so that the students could better relate the topic to outside problems. Our online learning platform allowed students to watch a variety of videos that helped illustrate different real-world statistical problems. In addition, the self-management project required students to apply course concepts to their own academic behavior, which certainly qualifies as a “real-world” situation. Cho and Shen also noted the importance of instructor scaffolding and self-regulated learning training prior to the course. By scaffolding, the instructor can monitor the behaviors of his/her students, and make changes to the structure of the class to better promote social interactions. The use of Piazza allowed us to do just this. Furthermore, in one class, students were required to read self-regulation and self-management techniques in the first week of the course. Cho and Shen found that students who were exposed to training in self-regulated learning utilized message boards as a form of communication better than students who did not receive such training.

Motivation and self-regulation are important aspects of self-guided behavior and self-control in order to achieve success in the classroom (Mezo, 2009; Pintrich & De Groot, 1990). Pintrich and De Groot (1990), in a correlational study, determined that motivation within the classroom comprises three factors: self-efficacy, intrinsic value, and test anxiety. These authors found moderately strong positive correlations between self-efficacy and intrinsic value with self-regulation. They also found a fairly weak negative correlation between test anxiety and self-regulation (Pintrich & De Groot, 1990). Pintrich (1999) also expanded on these findings in a later review of the literature. Pintrich concluded that while "self-regulated learning is neither easy nor automatic" (p. 467) in order to be self-regulated learners, students must be motivated to learn and develop useful strategies guided to more productive learning habits. In order to develop these strategies, students must hold high levels of self-efficacy, task value, and be mastery goal oriented. Having heightened levels of self-efficacy allows students to be confident in their learning (Pintrich, 1999) and use self-efficacy as a resource to combat difficult tasks (Bandura, 1986). Having a higher value of the task and learning in general, enable students to focus harder on the task at hand, ignoring less important stimuli and distraction (Pintrich, 1999). Lastly, students who set goals to master the content are more likely to engage in metacognitive processes, which improve learning and comprehension. Pintrich (1999) noted that these three elements of self-regulated learning have direct links to the motivation.

Motivation

In discussing motivation, it is important to consider understand the influence of different types of motivation in encouraging and maintaining academic behavior. Researchers (e.g., Ryan & Deci, 2000) have described at least two types of motivation related to academic behavior based on the source of the rewards that come from that behavior: intrinsic and extrinsic. Closely related to the concepts of intrinsic and extrinsic goal orientation, intrinsic and extrinsic motivation refer to valuing and working for rewards that come from doing a task for its own sake or that come some other source and that are not an inherent part of the task itself, respectively. Intrinsic motivation can be directly related to dispositional factors discussed by Onwuegbuzie and Wilson (2004). Like intrinsic goal orientation, intrinsic motivation has been argued to produce superior learning outcomes and to maintain learner interest in a task compared to extrinsic motivation (e.g., Ryan & Deci, 2000). In fact, some researchers (e.g., Kohn, 1996; Ryan & Deci, 1996) have argued that extrinsic motivation (or extrinsic rewards, such as points) can actually damage learners' intrinsic motivation, thereby reducing their interest in a task or topic and their desire to continue working on that task or learning that topic. Clearly, if this is true, then providing extrinsic rewards such as points for academic behavior seems ill advised. However, students may not always come into a course with strong (or any) intrinsic motivation to learn the course material (Deci & Ryan, 2000), and it could be argued that these students do not have any intrinsic motivation that could possibly be damaged by the use of external rewards. This is certainly often the case with students in introductory (and more advanced) statistics courses (S. Laraway, personal communication). Indeed, the high levels of students' statistics anxiety observed in many studies demonstrate that most students are not intrinsically motivated to study statistics.

Although the study of the effects of extrinsic rewards on intrinsic motivation has been ongoing for the past 40 years, there still remains a debate regarding the robustness of these effects and the conditions under which they occur. In their meta-analysis of the relevant literature, Cameron and Pierce (1994) noted that the data on this topic are far from conclusive and that the conditions under which extrinsic rewards reduce intrinsic motivation are fairly limited and easily avoided. They also found that when rewards are linked to meeting or exceeding a given level of performance these rewards can actually increase a person's interest in that activity (i.e., enhance intrinsic motivation). They proposed that this occurs because the extrinsic rewards provide useful feedback to the individual, thereby promoting self-reflection on his or her accomplishment and mastery of the task. Given that most students in statistics classes start the class with no intrinsic interest in taking it, we did not worry that extrinsic rewards in the form of points for completing a certain level of mastery on assignments would have any negative effects on their intrinsic motivation to learn the course material.

In this study, our main goal was to help students improve their ability to self-regulate in this online statistics course. We hoped that in doing so we would improve their class performance. A secondary goal was to encourage student engagement in the course by providing points for posting original questions and answers to other students' questions. Our study used a non-equivalent group design in which introductory statistics students who did not complete a self-management project were compared to introductory students in another who did complete a self-management project. We also used a single-case reversal (ABA) design to compare the number of student postings as a function of contingent point delivery in the class with the self-management project. We collected data on a number of different variables, including statistics anxiety, academic motivation, self-management/motivation, technology use, and digital literacy as possible covariates of student performance.

Method

Participants

Fifty-four students enrolled in two online sections of Elementary Statistics (STAT 95) at SJSU provided performance and engagement data for this study. Only those students who completed all exams in each section were included in the performance data. Of these students, thirty-eight also provided data on questionnaires measuring possible covariates of performance. One student was removed from the data set because he/she was under the age of 18 and we did not obtain parental consent. Participants' reported ages ranged from 18 to 41 ($M = 21.37$, $SD = 4.54$). Participants' reported gender was 22 females and 16 males. Participants' grade level ranged from freshman to graduate student (4 freshman, 8 sophomore, 11 junior, 11 senior, 3 graduate, and 1 other). The race/ethnicity of participants was 13 White, 4 Black, 11 Asian, 8 Hispanic, and 2 Other. Of those participants who answered the questionnaires, all were matriculated students at either SJSU or another California State University (CSU) campus (36 SJSU and 2 other CSUs) during either the summer 2014 session or the fall 2014 semester [17 in summer

2014 (Su14) and 21 in fall 2014 (Fa14)]. Data regarding participants' previous experience with mathematics, statistics, and online courses can be viewed in Table 1.

Table 1
Means and standard deviations of students' previous experience

Variable	Summer 2014 M (SD)	Fall 2014 M (SD)
Undergraduate units completed	69.12 (32.28)	58.02 (46.07)
Undergraduate statistics/research method courses completed	0.76 (1.03)	0.48 (0.81)
Number of math classes taken in high school	3.76 (0.44)	3.71 (0.78)
Number of statistics classes taken in high school	0.24 (0.44)	0.24 (0.44)
Number of online courses taken	1.53 (1.66)	1.95 (3.49)
	f (%)	f (%)
Taking Stat 95 for the first time	11 (64.7)	17 (81)

Note. f = frequency. % = percentage of students that are taking Stat 95 for the first time. Summer 2014 N = 17. Fall 2014 N = 21.

All enrolled students in the respective STAT 95 sections were notified through Canvas email at the beginning of the semester that they had the opportunity to participate in a study on motivation and self-regulated learning in online classes. Posted notes on the course discussion board (Piazza) and emails informed them that they could complete questionnaires regarding academic motivation, use and understanding of technology (digital literacy), statistics anxiety, self-management, motivation to take the course, and basic demographic questions (see descriptions of questionnaires below). A consent form was attached to the instruction page of each research survey. Participants were told that starting any survey indicated their agreement to participate in the study. Participation was completely voluntary, and participants were free to withdraw at any time without any negative effects towards their grades or relationship with SJSU. All participants earned extra credit as compensation for completing each questionnaire. Students who chose not to participate could perform an alternative activity for the same number of extra credit points.

Once the classes were completed, all class performance data were anonymized by removing student identification information (i.e., names, student identification numbers). Performance data for students who did not choose to answer the surveys were analyzed as archival data. This study was approved by the SJSU Institutional Review Board.

Materials

Canvas. Canvas is an online learning management system used by over 1,400 colleges, universities, and school districts (http://www.canvaslms.com). Both the Su14 and Fa14 Stat 95 courses were delivered completely through Canvas. Canvas allows instructors to create different modules that consist of quizzes, exams, homework assignments, surveys, lecture material, etc. Canvas is also equipped with third-party applications to help instructors modify and customize the student-learning environment. Students logged into Canvas at: https://sjsu.instructure.com/login.

Piazza. Piazza (www.piazza.com) is a start-up company that provides an online discussion board platform that we utilized as a third-party application running in Canvas. Piazza allows instructors to manage student questions and answers in a wiki-style format. In Piazza, students were free to post questions regarding course content, technical issues, assignment instructions, etc. Students could also answer other students' questions. Piazza allows instructors and TAs to endorse student questions and answers. Each question can be organized through different topics and the week in which it was asked.

Udacity. Udacity (http://www.udacity.com) is a for-profit educational start-up company that provides online courses in a variety of technology-related areas (e.g., data science, web development, mobile application development). We used the Udacity online platform to deliver the main course material (i.e., video lessons with embedded quizzes and practice problems) to the students enrolled in the Su14 session. The Udacity course (https://www.udacity.com/course/intro-to-descriptive-statistics--ud827 and https://www.udacity.com/course/intro-to-inferential-statistics--ud201) was authored by Dr. Ron Rogers (Professor and current Chair of the SJSU Department of Psychology) and Dr. Sean Laraway (Associate Professor in the Department of Psychology and instructor for the two sections of STAT 95 included in this study). Both classes covered 16 topics ranging from "Introduction to Statistical Research Methods" to "Chi-Squared Tests." Each lesson contained a number of short videos followed by interactive activities. The interactive activities required the students to complete a statistics problem in order to move on to the next video. The Udacity platform also had problem sets for each lesson and review problem sets at the end of each module.

Su14 students were required to use both the Canvas and Udacity platforms. For the Fa14 section, the Udacity videos were imported into Canvas; thus, for the Fa14 students, all material that the Su14 students received was delivered in Canvas (as a single learning platform). Several Udacity problem set questions did not get ported over properly in the Fa14 section because Canvas did not support some of the question formats.

It is important to note that the interactive activities after each video were not included in the Fa14 class. Although these changes may have a negative impact on the effectiveness of the Udacity lecture material, we feel that moving the Udacity content to Canvas made the overall course easier to access for students in the Fa14 class. Logging into the Udacity site was not required, although a small number of students chose to do so (S. Laraway, personal communication).

Measures

All students were asked to complete seven research questionnaires at the beginning of the semester, during an "Engagement Week" during which students were exposed to orientation materials but not actual course content. The questionnaires were titled and administered online through Canvas in the following order: (a) statistics anxiety, (b) academic motivation, (c) self-management, (d) class motivation, (e) technology use, (f) digital literacy, and (g) demographics. There were a total of 160 items across all research surveys. Participants were given one week to complete all of the research surveys. All measures were recorded online in the courses' Canvas site. Participants were given unlimited time to complete each questionnaire, as long as they completed them before the end of the first week of class.

Demographic survey. The demographic questionnaire consisted of 15 items. Participants were asked to answer questions about their background and to choose the answer that best describes them. We collected a variety of different demographic information such as age, gender, college major, college minor, college grade level, and race/ethnicity. Questions were delivered in both open-ended and close-ended response formats. For example, age and college major and minor were open-ended. Questions asking for gender, college grade level, and race/ethnicity, where close-ended. See Appendix A for the complete demographic questionnaire.

Student motivation and self-regulation. Student motivation and self-regulation was measured using the *Motivated Strategies for Learning Questionnaire* (MSLQ; Pintrich & De Groot, 1990). The MSLQ is a 44-item self-report instrument that measures students' motivational beliefs and self-regulated learning strategies (Pintrich & De Groot, 1990). Motivational beliefs are divided into three dimensions (i.e., *self-efficacy*, *intrinsic value*, and *test anxiety*). Self-regulated learning strategies are divided into two dimensions (*cognitive strategy use* and *self-regulation*). Each item is measured on a 1 to 7 Likert-type scale (where 1 = Not at all true of me; 3 = Somewhat true of me; 5 = True of me; and 7 = Very true of me), but due to a computer glitch each item was scaled on a 1 to 5 Likert-type scale (where 1 = Not at all true of me; 3 = Somewhat true of me; and 5 = Very true of me) in the present study. Although this error may have some effects on our results, we feel the impact would be minor. Some examples of the motivational beliefs items include; "Compared with other students in this class I expect to do well" (*self-efficacy*), "Understanding this subject is important to me" (*intrinsic value*), "I worry a great deal about tests" (*test anxiety*). Some examples of the self-regulated learning strategies items include; "When I study for a test I try to remember as many facts as I can," "When I am study a topic, I try to make everything fit together" (*cognitive strategy use*), and "I work on practice exercises and answer end of chapter questions even when I don't have to" (*self-regulation*). Out of the 44 items, there are four reverse-scored items

(items 26, 27, 37, and 38). The MSLQ is scored by taking the mean of the items in each of the five dimensions. Previous research has found the multiple dimensions of the MSLQ scale to be a valid measure of student motivation and self-regulation, as well as significant predictive validity for course grade (Pintrich et al., 1993). In this study, the overall MSLQ had a Cronbach's alpha value of .82. The Cronbach's alpha values for the self-efficacy, intrinsic value, test anxiety, cognitive strategy use, and self-regulation subscales were .76, .72, .83, .67, and .70, respectively. See Appendix B for the complete MSLQ questionnaire.

We also created a 10-item self-report questionnaire (titled *Motivation to Take this Class*) that identifies and measures different reasons for taking the class. Participants were given instruction to identify how important each of reasons was in their decision to enroll in the course. The motivation scale was measured using a 5-point, Likert-type scale (where 1 = Not important; 3 = Moderately important; 5 = Very important). Some examples of the items include; "I thought it would be fun and enjoyable," “The course fulfills General Education credit," and "I wanted to extend my knowledge of the topic." Item 10 of the questionnaire was an open-ended response format asking the participant to indicate any other reason they chose to enroll in the course. See Appendix C for the complete questionnaire.

Student self-management. Student self-management was measured using the *Self-Control and Self-Management Scale* (SCMS; Mezo, 2009). The SCMS is a 16-item self-report instrument that measures for self-control and self-management skills (SCMSk) in adults. The SCMS is broken down into 3 subscales of SCMSk: self-management (SM), self-evaluating (SE), and self-reinforcing (SR). Participants were given instruction to indicate how well each statement describes them. Each item was measured on a 5-point, Likert-type scale (where 1 = Not at all true of me; 3 = Somewhat true of me; and 5 = Very true of me). Some examples of the items include: "When I work toward something, it gets all my attention;" "I make sure to track my progress regularly when I am working on a goal," and "I give myself something special when I make some progress." Out of the 16 items, there are five reverse-scored items (items 7, 8, 9, 10, and 11) that are used as a measure of SE. Previous research has found the SCMS to have a 0.81 coefficient alpha and a 0.75 test-retest correlation coefficient (SCMS; Mezo, 2009, see Appendix D for the complete SCMS questionnaire). In the present study, Cronbach's alpha for the SCMS was .73. The Cronbach's alpha for the self-management, self-evaluating, and self-reinforcing subscales were .74, .77, and .84, respectively.

Digital literacy and technology use. Digital literacy questions were used to measure participants' use of, and familiarity with, common technologies related computer and Internet use. Technology use was measured using a 17-item, self-report questionnaire with a multiple-choice response format. Participants were given instruction to answer the following questions about their use of various technologies, including computers and the internet. See Appendix E for the complete Technology Use questionnaire. Digital literacy was measured using a 7-item, self-report questionnaire. Each item was measured on a 5-point, Likert-type scale (where 1 = No understanding; 3 = Some understanding; and 5 = Full understanding). Participants were given instruction to describe their familiarity with different Internet-related items (i.e., MP3 file, preference setting on web browser, refresh/reloading a web browser, Newsgroup, PDF file, Blog, and Spam). These items were modified from those described by Hargittai (2005). The Cronbach's alpha for the digital literacy questionnaire was .81. See Appendix F for the complete technology use and digital literacy questionnaire.

Statistics anxiety. Statistics anxiety was measured using the *Statistics Anxiety Rating Scale* (STARS; Cruise et al., 1985). The STARS is a 51-item, self-report instrument that measures for six subscales of statistics anxiety (i.e., worth of statistics, interpretation anxiety, test and class anxiety, computational self-concept, fear of asking for help, and fear of statistics teachers). Participants were given instruction to indicate how much each of the statements describes their feelings towards statistics. Each item was measured on a 5-point, Likert-type scale. The scale is divided up into two sections where half of the answers are reverse scored. The first section contains 23 items measuring for *interpretation anxiety*, *test and class anxiety*, and fear *of asking for help* (where 1 = Causes me very little anxiety and 5 = Causes me very much anxiety). The second section contained 28 items measuring for *worth of statistics*, *computational self-concept* and fear *of statistics teachers* (where 1 = Agree and 5 = Disagree). Some examples of items include: "I don't understand why someone in my field needs statistics" (*worth of statistics*), "Interpreting the meaning of a table in a journal article" (*interpretation anxiety*), "Studying for an examination in a statistics course" (*test and class anxiety*), "I could enjoy statistics if it weren't so mathematical" (*computation self-concept*), "Asking one of your professors for help in understanding a printout" (*fear of asking for help*), and "Statistics teachers are so abstract they seem inhuman" (*fear of* *statistics teachers*). We scored the STARS by taking the sum of each of the six subscale scores, such that higher scores indicate higher levels of statistics anxiety and lower scores indicate lower levels of statistics anxiety. Total scores can range from 51 - 255. Previous research has shown evidence of strong concurrent validity with other instruments of anxiety inventories and acceptable internal consistency reliability (Baloglu, 2002; Cruise et al., 1985; Onwuegbuzie, 1998). In this study, the Cronbach's alpha for the STARS was .94. The Cronbach's alpha values for the worth of statistics, interpretation anxiety, test and class anxiety, computational self-concept, fear of asking for help, and fear of statistics teachers subscales were .92, .87, .85, .64, .87, and .79, respectively. See Appendix G for the complete STARS questionnaire.

Student performance. Student performance was measured by taking the mean percent of correct answers on all quizzes and exams. Mean final grade (percentage) was also used as a measure of student performance. The final course grade was comprised of grades on quizzes, exams, participation, and the self-monitoring (Su14) or self-management (Fa14) project. In the Su14 class, there were a total of 16 quizzes and 3 exams. In the Fa14class, there were a total of 16 quizzes and 4 exams.

Procedure

Summer 2014 (Su14): goal setting and self-monitoring. For our control condition we used the summer 2014 Elementary Statistics (STAT 95) online session at SJSU. The instructor for the course was Dr. Sean Laraway. The course used two statistics coaches, who were graduate students who had previously taken Stat 95. This online session was a 10-week, 3-unit course. Students were required to login to two learning platforms (Canvas and Udacity) for the online material. The instructor held online chat sessions on Canvas every Sunday between 6 and 8 p.m. for the students to ask any questions they may have regarding the material. Students were also encouraged to ask questions at any time on Piazza. Among the lessons and problem sets hosted on Udacity, as well as quizzes and exams administered on Canvas, students were also required to complete a self-monitoring project. The self-monitoring project required the students to set goals regarding their academic behavior in this class and to monitor themselves by collecting data on three forms of academic behavior: minutes spent each day working on the course, number of problem set questions answered per day, and number of videos watched each day. Students had to enter their data in a Microsoft Excel© Data Sheet. This sheet was prepared by the instructor to compute descriptive statistics and create graphs of the raw data entered by the students. The descriptive statistics computed were the percentage of goals met, means, medians, and standard deviations of the other variables. Students were then required to complete a write-up on their reflection of how much time they put towards the course and provide a table of descriptive statistics for each variable for each week. Students also had to provide two line graphs for each of the three variables and a written description of their goals and performance. See Appendix H for the complete Su14 self-monitoring project guidelines.

Fall 2014 (Fa14): goal setting, self-monitoring, and self-management. For our quasi-experimental condition we used the fall 2014 Elementary Statistics (Stat 95) online session at SJSU. The instructor for the course was Dr. Sean Laraway. This class had the same statistics coaches as in the Su14 session. This online session was a 16-week, 3-unit course. The instructor held online chat sessions on Canvas every Thursday between 6 and 7 p.m. for the students to ask any questions they may have regarding the material. Students were also encouraged to ask questions at any time on Piazza. Students enrolled in this course were only required to log into Canvas. Unlike our control condition, we combined both learning platforms into a single learning platform. All problem sets and lesson videos from Udacity were imported into Canvas modules. All quizzes and exams were administered on Canvas. Students were also required to complete a self-management project that included a self-delivered behavioral intervention. The project had the same requirements as in our control condition (goal setting, self-monitoring) except students were also required to design an intervention to provide incentives for meeting goals and/or provide aversive consequences for not meeting goals based on the techniques described by Malott and Harrison (2006). The self-designed and self-delivered intervention required the students to list any consequences (incentives and/or aversives) they would use to change their own behavior. Students were also required to describe environmental changes that they hypothesized might affect their academic behavior. They also had to set deadlines for determining if the self-management system was effective. If the students determined that the self-management system was not helping them meet their goals, they were encouraged to "recycle" the intervention to improve its effectiveness. The number of behavioral measures that students needed to track was reduced to the minutes spent each day working on the course. This was meant to simplify the goal-setting and self-monitoring aspects of the project in hopes of improving data collection. In summary, the Su14 class engaged in goal setting and self-monitoring but did not design an intervention to change their academic behavior; this class recorded three measures of academic behavior. The Fa14 class engaged in goal setting, self-monitoring, and self-management by designing an intervention to deliver incentives for meeting goals or aversives for not meeting goals; this class recorded only one measure of academic behavior. See Appendix I for the complete FA14 self-management project guidelines.

ABA design. In the Fa14 class, we decided to provide incentives for student participation on Piazza. At the beginning of week 4 of the semester, we posted instructions on Piazza that explained that students could earn up to three participation points per week during a 5-week period. We awarded points to students for asking two original questions (not just repeating a question already posted) about the course material (statistical topics, not questions about assignments, etc.) and answering at least one question posted on Piazza by another student. An example of a counted question asked by a student is: "Can someone explain to me the null hypothesis in simpler terms? Would you agree to the null being described as a statement that has no relationship to anything? I am not sure if this would be a good way to think about it." An example of a question that was not counted is: "Will there be links to the statistical tables on the exam or will we need to print them ourselves for use?" The number of answers were not reported in the present study as they were just meant to give students something to do if they did not have any questions to ask. After the first two weeks, we noticed a lack of questions, so we reminded students of the participation announcement. For our ABA analysis we calculated number of questions asked by students each week for the entire 16-week period. To provide a baseline comparison, we also calculated the number of questions (statistics related) asked by students in the Su14 class.

Results

Descriptive Statistics

Student performance. Student performance was calculated by computing the mean of all quizzes, exams, and final grade (see Table 2). The percentage and frequency of students who completed each quiz and exam were also calculated as a measure of student engagement (see Tables 3 and 4, respectively). These data show attrition throughout the semester.

Table 2
Means and standard deviations for student performance variables

Performance Variable	Summer 2014 (n = 21) M (SD)	Fall 2014 (n = 33) M (SD)
Quiz grade	82.34 (8.44)	87.93 (8.48)
Exam grade	66.83 (13.16)	76.88 (12.54)
Final grade	78.95 (12.03)	84.39 (11.87)

Note. Final grades reflect differences in extra-credit given between both sections. Only students that completed every exam were included in these analyses.

Table 3
Percentage and frequency of students who completed exams

	Summer 2014 (n = 23)		Fall 2014 (n = 38)	
Exam number	f	%	f	%
Exam 1	21	91.3	38	100
Exam 2	22	95.65	37	97.37
Exam 3	21	91.3	33	86.84
Exam4	-	-	33	86.84

Note. f = frequency. % = percentage of students that completed the exam. Data includes all students who completed at least one exam. In the fall 2014 section, there was one extra exam (exam 4).

Table 4
Percentage and frequency of students who completed quizzes

	Summer 2014 (n = 23)		Fall 2014 (n = 39)	
Quiz number	f	%	f	%
Quiz 1	23	100	37	94.87
Quiz 2	23	100	37	94.87
Quiz 3	23	100	39	100
Quiz 4	23	100	39	100
Quiz 5	23	100	37	94.87
Quiz 6	23	100	38	97.44
Quiz 7	23	100	34	87.18
Quiz 8	23	100	37	94.87
Quiz 9	23	100	36	92.31
Quiz 10	22	95.65	36	92.31
Quiz 11	22	95.65	34	87.18
Quiz 12	23	100	34	87.18
Quiz 13	23	100	35	89.74
Quiz 14	21	91.3	36	92.31
Quiz 15	21	91.3	35	89.74
Quiz 16	20	86.96	34	87.18

Note. f = frequency. % = percentage of students that completed the quiz. Data includes all students who completed at least one quiz. In the summer 2014 section, quizzes 14 and 15 were administered as a single quiz.

Statistics anxiety. Statistics anxiety was calculated using the *Statistics Anxiety Rating Scale* (STARS). The STARS is broken down into 6 subscales (i.e., worth of statistics, interpretation anxiety, test and class anxiety, computational self-concept, fear of asking for help, and fear of statistics teachers). The means and standard deviations of the STARS scores are presented in Table 5.

Table 5
Means and standard deviations of Statistics Anxiety Rating Scale scores

Subscale	Summer 2014 *M* (*SD*)	Fall 2014 *M* (*SD*)
Worth of statistics (16 - 80)	41.94 (13.25)	38.00 (12.47)
Interpretation anxiety (11 - 55)	29.47 (7.78)	24.81 (8.78)
Test and class anxiety (8 - 40)	26.29 (6.67)	23.095 (7.02)
Computational self-concept (7 - 35)	19.41 (7.43)	18.38 (10.16)
Fear of asking for help (4 - 20)	9.41 (4.87)	7.19 (2.94)
Fear of statistics teachers (5 - 25)	10.82 (4.53)	11.095 (4.29)
Total score (51 - 225)	137.35 (35.38)	122.57 (33.46)

Note. Total range of possible scores are in parentheses next to each subscale. Summer 2014 $N = 17$. Fall 2014 $N = 21$.

Motivation and self-regulation. Student motivation was calculated in both the *Motivated Strategies for Learning Questionnaire* (MSLQ) and the *Motivation to Take this Class* questionnaire. The MSLQ is broken down into 2 subscales (i.e., motivational beliefs and self-regulated learning strategies). Each subscale is further broken down into subscales (i.e., self-efficacy, intrinsic value, test anxiety, cognitive strategy use and self-regulation). The means and standard deviations of the MSLQ scores are presented in Table 6. The second motivation scale is calculated by collecting a score (frequency and percentage) for each of the 10 motives. The frequencies and percentages of the *Motivation to Take this Class* scores are presented in Table 7.

Table 6

Means and standard deviations of Motivated Strategies for Learning Questionnaire scores

Subscale	Summer 2014 *M* (*SD*)	Fall 2014 *M* (*SD*)
Motivational Beliefs		
Self-efficacy	3.29 (0.58)	3.56 (0.48)
Intrinsic value	3.58 (0.52)	3.77 (0.46)
Test anxiety	3.10 (1.05)	3.46 (1.13)
Self-Regulated Learning Strategies		
Cognitive strategy use	3.68 (0.56)	3.67 (0.38)
Self-regulation	3.45 (0.69)	3.41 (0.48)

Note. Motivational Beliefs and Self-Regulated Learning Strategies are the two main domains of the MSLQ; the subscales of each domain are listed below. Summer 2014 N = 17. Fall 2014 N = 21.

Table 7

Means and standard deviations for Motivation to Take this Class questionnaire scores

Motive	Summer 2014 *M* (*SD*)	Fall 2014 *M* (*SD*)
Fun and enjoyable	3.53 (1.12)	2.67 (1.53)
Relevant in my academic field of study	4.00 (0.94)	3.76 (1.18)
Teaches skills that will help in my job/career	4.35 (0.61)	3.76 (1.22)
Curious to take an online course	2.94 (1.197)	2.38 (1.28)
Required for my degree	4.41 (0.94)	4.33 (1.28)
Fulfills general education credit	4.41 (0.94)	4.19 (1.50)
Couldn't get into another section of the course	1.47 (0.799)	2.86 (1.68)
Interested in the topic	2.82 (1.19)	2.57 (1.03)
To extend my knowledge of the topic	3.47 (1.23)	3.19 (1.33)

Note. Range of scores for each item was 1 - 5, with 1 = Not important and 5 = Very important. Summer 2014 N = 17. Fall 2014 N = 21.

Self-management. Student self-management was calculated using the *Self-Control and Self-Management Scale* (SCMS). The SCMS is broken down into 3 subscales (i.e., self-management, self-evaluating, and self-reinforcing). The means and standard deviations of the SCMS scores are presented in Table 8.

Table 8
Means and standard deviations of Self-Control and Self-Management Scale scores

Subscale	Summer 2014 *M* (*SD*)	Fall 2014 *M* (*SD*)
Self-management (SM) (6 - 30)	23.76 (4.09)	22.71 (3.16)
Self-evaluating (SE) (5 - 25)	21.06 (3.56)	20.33 (3.79)
Self-reinforcing (SR) (5 - 25)	18.29 (5.06)	18.38 (4.32)
Total score (16 - 80)	63.12 (9.00)	61.43 (5.71)

Note. Total range of possible scores are in parentheses next to each subscale. Summer 2014 $N = 17$. Fall 2014 $N = 21$.

Digital literacy and technology use. Technology use was calculated using a 17-item questionnaire with multiple choice format. Table 9 contains the frequencies, percentages, means and standard deviations for the technology use questionnaire. Digital literacy was calculated using a 7-item questionnaire measuring the participants' level of understanding for each digital item (i.e., MP3 file, preference setting on a web browser, refresh/reload on a web browser, newsgroup, PDF file, blog, and spam). The means and standard deviations for each of the items are presented in Table 10.

Table 9

Frequencies and percentages for technology use questionnaire scores

Technology use	Summer 2014 f (%)	Fall 2014 f (%)
Computer use at work for non-work purposes*	8 (47.1)	10 (47.6)
Internet use at home	16 (94.1)	21 (100)
Online at least once per day	16 (94.1)	21 (100)
High-speed internet access at home	16 (94.1)	21 (100)
Have a smart phone	17 (100)	21 (100)
Use smart phone to access internet*	17 (100)	21 (100)
Use the web to make purchases	15 (88.2)	18 (85.7)
Use the web for financial purposes	16 (94.1)	21 (100)
Play online games	7 (41.2)	10 (47.6)
Use social media sites (e.g., Facebook, Instagram, Pintrerest)	17 (100)	20 (95.2)
Regular use of search engines (e.g., Google, Yahoo!)	17 (100)	21 (100)
Regular access to computer at home	16 (94.1)	21 (100)
Own a tablet computer	5 (29.4)	9 (47.4)
Used the internet for the following information**	17 (100)	21 (100)
	M (*SD*)	*M* (*SD*)
Years used the web	11.71 (3.22)	10.86 (4.65)
Average hours per day spent on the internet	4.07 (2.30)	4.19 (2.56)
Average hours per day spent using a computer	3.82 (2.79)	4.48 (3.42)

Note. f = frequency. % = percentage of participants that use the technology. *Multiple choice format allowed students to answer yes, no, and not applicable. **Participants were asked to mark all that apply for internet use to read or learn about: (1) national news, (2) international news, (3) sports, (4) political information, (5) health information, (6) financial information, (7) government services, (8) product information, (9) online purchases.

Table 10

Means and standard deviations of digital literacy questionnaire scores

Digital items	Summer 2014 *M* (*SD*)	Fall 2014 *M* (*SD*)
MP3 file	3.94 (1.25)	3.90 (1.18)
Preference settings	4.18 (1.01)	3.90 (1.00)
Refresh/Reload	4.82 (0.73)	4.81 (0.51)
Newsgroup	2.59 (1.23)	2.95 (1.24)
PDF file	4.59 (0.62)	4.38 (1.02)
Blog	4.06 (1.09)	4.14 (0.91)
Spam	3.76 (1.25)	4.33 (0.86)

Note. Range of scores for each item was 1 - 5, with 1 = No understanding and 5 = Full understanding. Summer 2014 $N = 17$. Fall 2014 $N = 21$.

Between-Group Analyses

Student performance. Multiple independent samples *t* tests were conducted to compare student performance between the Su14 and Fa14 classes. Students in Fa14 earned higher average quiz grades ($M = 87.93$, $SD = 8.48$) than did students in Su14 ($M = 82.34$, $SD = 8.44$). Students in Fa14 also earned higher average exam grades ($M = 76.88$, $SD = 12.54$) than did students in Su14 ($M = 66.83$, $SD = 13.16$). Students in Fa14 earned higher average final grades ($M = 84.39$, $SD = 11.87$) than did students in Su14 ($M = 78.95$, $SD = 12.03$), although results were not significant. Independent samples *t* test data for student performance variables are presented in Table 11.

Table 11

Independent samples t test for student performance

Performance variable	*t*	*df*	*p*	*d*
Quiz grade	-2.37	52	.022*	-.66
Exam grade	-2.82	52	.007*	-.78
Final grade	-1.63	52	.109	-.05

Note. d = Cohen's d. * $p < .05$

Covariates. In order to determine the extent to which the two classes where similar before the students were exposed to statistics content, multiple independent samples *t* tests were conducted for each of the questionnaires as covariates (i.e., STARS, MSLQ, motivation to take the class, SCMS, Technology Use, and Digital Literacy). All independent samples *t* test data for the questionnaires are presented in Tables 12 - 16.

Table 12

Independent samples t test for the Statistics Anxiety Rating Scale

Subscale	*t*	*df*	*p*	*d*
Worth of statistics (16 - 80)	.94	36	.352	.31
Interpretation anxiety (11 - 55)	1.71	36	.096	.57
Test and class anxiety (8 - 40)	1.43	36	.162	.48
Computational self-concept (7 - 35)	.35	36	.729	.12
Fear of asking for help (4 - 20)	1.65	25.09	.111	.66
Fear of statistics teachers (5 - 25)	-.19	36	.851	-.06
Total score (51 - 225)	1.32	36	.195	.44

Note. *d* = Cohen's *d*. Fear of asking for help subscale was significant for Levene's Test of Equality of Variances

Table 13

Independent samples t test for the Motivated Strategies for Learning Questionnaire

Subscale	*t*	*df*	*p*	*d*
Motivational Beliefs				
Self-efficacy	-1.51	36	.139	-.50
Intrinsic value	-1.19	36	.241	-.40
Test anxiety	-1.01	36	.319	-.34
Self-Regulated Learning Strategies				
Cognitive strategy use	.09	36	.933	.03
Self-regulation	.23	36	.821	.08

Note. *d* = Cohen's *d*. Total Score was significant for Levene's Test of Equality of Variances.

Table 14

Independent samples t test for the Motivation to Take this Class questionnaire

Motive	*t*	*df*	*p*	*d*
Fun and enjoyable	1.94	36	.060	.65
Relevant in my academic field of study	.68	36	.503	.23
Teaches skills that will help in my job/career	1.94	30.51	.061	.70
Curious to take an online course	1.38	36	.177	.46
Required for my degree	.21	36	.834	.07
Fulfills general education credit	.53	36	.601	.18
Couldn't get into another section of the course	-3.34	29.83	.002*	-1.22
Interested in the topic	.70	36	.487	.23
To extend my knowledge of the topic	.69	36	.508	.23

Note. d = Cohen's d. Motives: "Teaches skills that will help in my job/career" and "Couldn't get into another section of the course" were both significant for Levene's Test of Equality of Variances. $*p < .05$

Table 15

Independent samples t test for the Self-Control and Self-Management Scale

Subscale	*t*	*df*	*p*	*d*
Self-management (SM) (6 - 30)	.89	36	.377	.30
Self-evaluating (SE) (5 - 25)	.60	36	.550	.20
Self-reinforcing (SR) (5 - 25)	-.06	36	.955	-.02
Total score (16 - 80)	.70	36	.486	.23

Note. d = Cohen's d.

Table 16

Independent samples t test for the digital literacy questionnaire

Digital items	*t*	*df*	*p*	*d*
MP3 file	.09	36	.927	.03
Preference settings	.83	36	.412	.28
Refresh/Reload	.07	36	.945	.02
Newsgroup	-.90	36	.373	-.30
PDF file	.73	36	.468	.24
Blog	-.26	36	.797	-.09
Spam	-1.60	27	.122	-.61

Note. d = Cohen's d. Spam was significant for Levene's Test of Equality of Variances.

Correlation analyses. Multiple Pearson r correlation coefficients were computed to identify any relationship between the questionnaire data and student performance. Analyses were conducted for each class separately and for both classes combined. The correlation analyses are presented in Tables 17 - 22.

Table 17

Correlation analysis for the Statistics Anxiety Rating Scale (all participants)

Subscale	Quiz Grade	Exam Grade	Final Grade
Worth of statistics	-.22 (.05)	-.33* (.11)	-.30 (.09)
Interpretation anxiety	-.29(.08)	-. 38* (.14)	-.35* (.12)
Test and class anxiety	-.17 (.03)	-.44** (.19)	-.37* (.13)
Computational self-concept	.05 (.00)	-.09 (.01)	-.05 (.00)
Fear of asking for help	-.16 (.03)	.05 (.00)	.06 (.00)
Fear of statistics teachers	-.07 (.01)	-.18 (.03)	-.19 (.04)
Total score	-.20 (.04)	-.34* (.12)	-.30 (.09)

Note. $N = 38$. Numbers in parenthesis are r^2 values. $*p < .05$ $**p < .01$

Table 18

Correlation analysis for the Statistics Anxiety Rating Scale (each semester)

	Summer 2014			Fall 2014		
Subscale	QG	EG	FG	QG	EG	FG
Worth of statistics	-.11 (.01)	-.51* (.26)	-.44 (.20)	-.26 (.07)	-.10 (.01)	-.11 (.01)
Interpretation anxiety	.04 (.00)	-.54* (.29)	-.39 (.15)	-.44* (.19)	-.12 (.02)	-.20 (.04)
Test and class anxiety	.13 (.02)	-.32 (.11)	-.15 (.02)	-.28 (.08)	-.44* (.19)	-.44* (.20)
Computational self-concept	.00 (.00)	-.25 (.06)	-.19 (.04)	.22 (.05)	.04 (.00)	.07 (.01)
Fear of asking for help	.02 (.00)	.25 (.06)	.24 (.06)	-.05 (.00)	.14 (.02)	.10 (.01)
Fear of statistics teachers	.17 (.03)	-.07 (.00)	-.02 (.00)	-.51* (.26)	-.34 (.12)	-.38 (.15)
Total score	.02 (.00)	-.40 (.16)	-.29 (.09)	-.27 (.08)	-.18 (.03)	-.21 (.04)

Note. QG = quiz grade. EG = exam grade. FG = final grade. Numbers in parenthesis are r^2 values. Summer 2014 $N = 17$. Fall 2014 $N = 21$. $*p < .05$

Table 19

Correlation analysis for the Motivated Strategies for Learning Questionnaire (all participants)

Subscale	Quiz Grade	Exam Grade	Final Grade
Motivational Beliefs			
Self-efficacy	.14 (.02)	.08 (.01)	.04 (.00)
Intrinsic value	.21 (.04)	.13 (.02)	.14 (.02)
Test anxiety	-.00 (.00)	-.35* (.12)	-.31 (.09)
Self-Regulated Learning Strategies			
Cognitive strategy use	.00 (.00)	-.14 (.02)	-.05 (.00)
Self-regulation	-.12 (.01)	-.12 (.01)	-.06 (.00)

Note. $N = 38$. Numbers in parenthesis are r^2 values. $*p < .05$

Table 20

Correlation analysis for the Motivated Strategies for Learning Questionnaire (each semester)

	Summer 2014			Fall 2014		
Subscale	QG	EG	FG	QG	EG	FG
Motivational Beliefs						
Self-efficacy	-.12 (.02)	-.02 (.00)	-.08 (.02)	.22 (.05)	-.04 (.00)	-.01 (.00)
Intrinsic value	.11 (.01)	.11 (.01)	.20 (.04)	.15 (.02)	-.00 (.00)	-.03 (.00)
Test anxiety	.01 (.00)	-.55* (.31)	-.45 (.20)	-.29 (.08)	-.41 (.17)	-.36 (.13)
Self-Regulated Learning Strategies						
Cognitive strategy use	.01 (.00)	-.14 (.02)	-.05 (.00)	.02 (.04)	-.16 (.03)	-.05 (.00)
Self-regulation	-.16 (.03)	-.21 (.05)	-.16 (.03)	-.04 (.00)	.01 (.00)	.10 (.01)

Note. QG = quiz grade. EG = exam grade. FG = final grade. Numbers in parenthesis are r^2 values. Summer 2014 $N = 17$. Fall 2014 $N = 21$. $*p < .05$

Table 21
Correlation analysis for the Self-Control and Self-Management Scale (all participants)

Subscale	Quiz Grade	Exam Grade	Final Grade
Self-management	.06 (.00)	-.06 (.00)	.02 (.00)
Self-evaluating	-.22 (.05)	-.06 (.00)	-.09 (.01)
Self-reinforcing	.13 (.05)	.12 (.01)	.13 (.02)
Total score	-.00 (.00)	.01 (.00)	.05 (.00)

Note. $N = 38$. Numbers in parenthesis are r^2 values.

Table 22
Correlation analysis for the Self-Control and Self-Management Scale (each semester)

	Summer 2014			Fall 2014		
Subscale	QG	EG	FG	QG	EG	FG
Self-management	.11 (.01)	-.16 (.03)	-.09 (.01)	.30 (.09)	.17 (.03)	.26 (.07)
Self-evaluating	-.22 (.05)	.32 (.10)	.17 (.03)	-.21 (.04)	-.29 (.08)	-.23 (.05)
Self-reinforcing	.13 (.02)	.20 (.04)	.30 (.09)	.18 (.03)	.06 (.00)	-.03 (.00)
Total score	.04 (.00)	.17 (.03)	.20 (.04)	.16 (.03)	-.05 (.00)	-.03 (.00)

Note. QG = quiz grade. EG = exam grade. FG = final grade. Numbers in parenthesis are r^2 values. Summer 2014 $N = 17$. Fall 2014 $N = 21$.

Within-Subject (ABA) Analysis

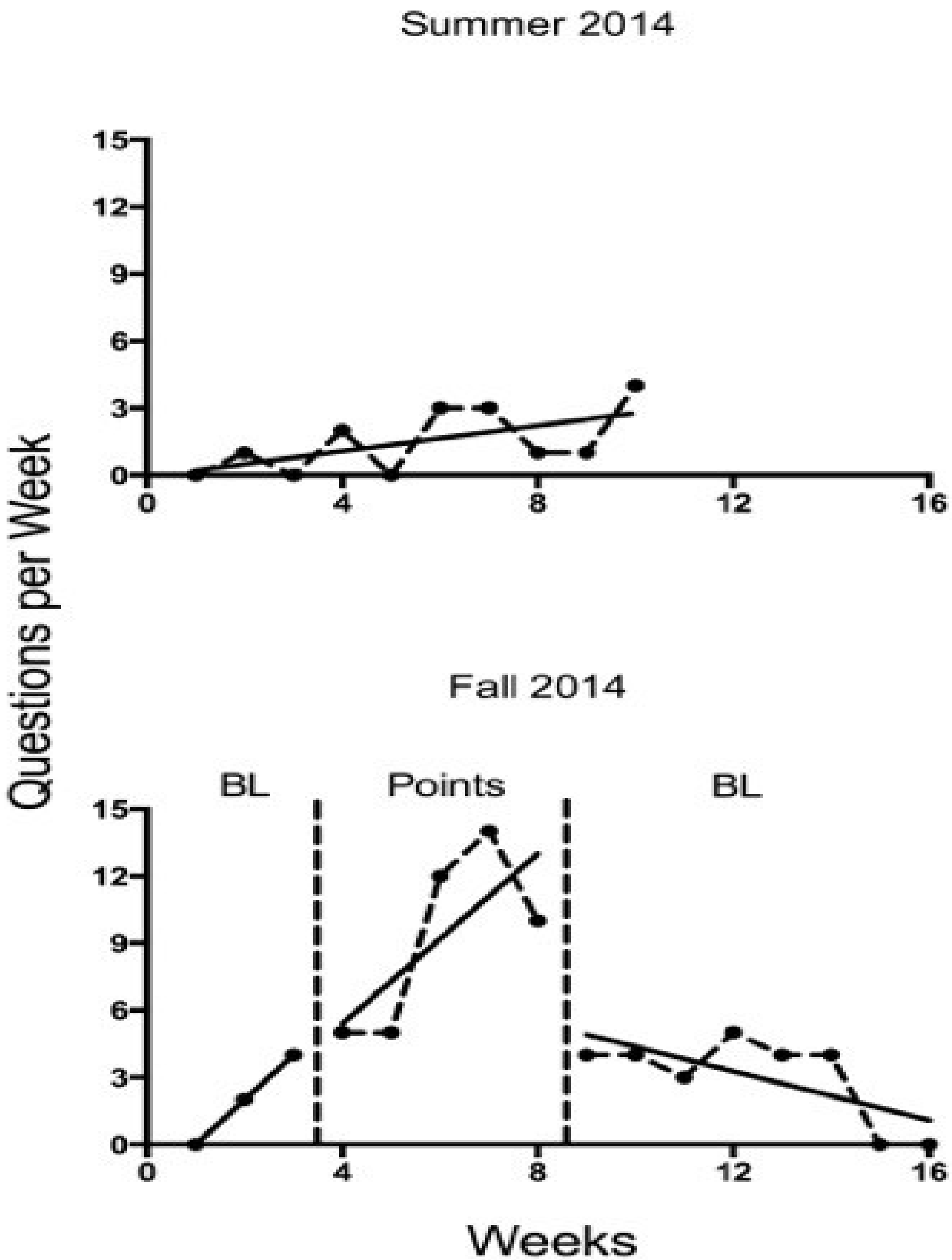
There were a total 79 statistics related questions asked in the Fa14 class; 51.52% of the students asked at least one statistics related question. To provide a comparison, there were a total of 15 statistics related questions asked in the Su14 class; 23.81% of the students asked at least one statistics related question. Linear regression analysis of the data in the ABA design using the methods described by Huitema (2011, Ch.20) was conducted on the number of questions asked by the students each week in the Fa14 class. Figure 1 depicts these data (bottom panel); for comparison, the same type of data for the Su14 class are included in the top panel. The coefficients for the regression analysis appear in Table 23. The overall model was statistically significant, $F(5,10) = 9.20$, $p = .002$, $R^2 = .82$. The residuals appear to be normally distributed and the lag-1 autocorrelation coefficient was -.08, indicating that the residuals showed a negligible amount of autocorrelation (Huitema, 2011, p. 382, suggested a cutoff of .30 for small *N* studies).

Table 23
ABA analysis

Term	Coefficient	*t*	*p*
Level change 1 (β2)	-0.60	-0.17	.871
Slope change 1 (β3)	-0.10	-0.06	.952
Level change 2 (β4)	-9.98	-3.86	.003*
Slope change 2 (β5)	-2.45	-3.31	.008*
Intercept (Constant)	-2.00	-0.62	.547

Note. **p* <.05

Figure 1
ABA plots



Note. X-axis depicts weeks. Y-axis depicts number of questions asked.

Discussion

Interpretation

The primary purpose of the present study was to identify any positive effects on grades by having a self-management project embedded within an online statistics course. A secondary purpose was to examine the effects of providing contingent points on the number of questions posted to the course discussion board. The present study consisted of both a between-subject design and a within-subject design. For our between-subject quasi-independent variable we had one of the classes (Su14) set goals for their class-related academic behavior and track those behaviors (goal-setting and self-monitoring). The other class (Fa14) set goals and tracked their study behaviors *and* arranged self-delivered consequences (self-reinforcement and/or self-punishment). For our within-subject independent variable (specific to the Fa14 class) we awarded students with participation points for asking and answering questions during a mid-semester period of 5 weeks (ABA design) in order to identify any change in behavior after giving an incentive to ask/answer questions. We measured three primary dependent variables measuring student performance (i.e., quiz, exam, and final grade). Finally, our participants completed multiple questionnaires administered at the beginning of each class in order to measure group equivalence and identify any covariates that may predict student performance. Overall, the main goal of our study was to help students understand and improve their self-regulation skills with respect to their academic behavior in an online statistics course with the hope of improving student performance.

Online courses are rapidly growing in popularity and it is imperative that university professors understand that students may not be prepared for the structure of an online course. Online courses require students to set goals, understand their own capabilities, and reflect on their self-management skills. In a traditional face-to-face seminar/lecture course, class times are set, assignments have specific due dates and times, and students are somewhat forced to intermingle with other students. Online courses do not have these features, and it is up to the students to use the tools given by the online infrastructure to communicate with the instructor and other students while maintaining a healthy pace as they work through the course. We understand that these variables affect student performance in an online course, and one of our goals was to identify any variables that predict poor student performance in an online course.

Correlation analyses. The Statistics Anxiety Rating Scale (STARS) was used to measure statistics anxiety in the students before they had seen any of the statistics related content. As seen in Table 17, when looking at all of the participants from both classes ($n = 38$), we found that on three of the six subscales (i.e., worth of statistics, interpretation anxiety, and test and class anxiety) of the STARS, there was a significant (moderately low, -.33 to -.44) negative relationship between statistics anxiety and exam grade. Furthermore, we found that there was a significant (moderately low, -.34) negative relationship between the total score on the STARS and exam grade. Interestingly, there were no significant results for computational self-concept, fear of asking for help, and fear of statistics teachers. However, when looking specifically at the Fa14 class, results indicate a significant (medium, -.51) negative relationship between fear of statistics teachers and quiz grade. These findings suggests that students who score higher on the STARS (i.e., increased statistics anxiety and negative attitudes towards statistics), may perform more poorly on exams and, in some cases, quizzes and final grade. When looking at specifically the Fa14 class and the relationship between scores on the STARS and student performance, Test and class anxiety was found to have a significant (medium, -.44) negative relationship with both exam grade and final grade. Interestingly, interpretation anxiety was the only other subscale in the Fa14 class that had a significant (medium, -.44) negative relationship with quiz grade. On the other hand, the Su14 class had two significant (medium, -.51 and -.54) negative relationships between worth of statistics and interpretation anxiety with exam grade. Overall our results indicate that negative attitudes towards statistics and statistics anxiety are related to student performance.

Another variable that we thought might predict student performance was the Motivated Strategies for Learning Questionnaire (MSLQ). As seen in Table 19, when looking at all participants from both classes *(n* = 38), we found that only one of the subscales of the MSLQ (i.e., test anxiety) had a significant (moderately low, -.35) negative relationship with exam grade. When looking at each class, there were no significant relationships found. These results indicate that overall the MSLQ was not useful in predicting student performance. However, given that the only subscale that showed significance was test anxiety, it is not surprising that this would be the one subscale that showed significance based on the similarity of items with the STARS. It is important to note that the lack of relationships between the MSLQ subscales and our performance variables might have been due to the way we scored the MSLQ. In previous studies, the questionnaire was scored on a 7-point, Likert-type scale; we used a 5-point, Likert-type scale. Although this may have minor impact on the questionnaire results, it is still a concern when looking at the lack of findings from the MSLQ. It is also important to point out that the variables that were not significantly related to performance were self-regulation, self-efficacy, and intrinsic value (motivation) constructs, but *not* anxiety.

We also did not find any evidence that the Self-Control and Self-Management Scale (SCMS) variables significantly predicted student performance in the entire sample of participants or in each individual section. After seeing a lack of significant findings for both the SCMS and the self-regulation, self-management, and motivation subscales of the MSLQ, it may be the case these variables are not as important as predictors as are those that measure test and class anxiety. This interpretation is supported by the relatively small correlations (and r^2 values) seen with the variables that did not measure anxiety. It is also possible that our students had the tendency to identify themselves as having better self-regulation/management skills than they really had and/or mark answers more towards the middle of the scale, whereas with anxiety measures, students may have been more willing to answer these questions with more extreme values (1 and 5). A main limitation of the current study is the lack of post-class questionnaire for each of the surveys administered. If we had collected post-test data, we might have observed changes in these variables, which would have helped us make stronger comparisons of the two classes. We predict that the Fa14 class would have shown positive effects on the variables related to self-regulation after experiencing the self-reinforcement component of the self-management project, whereas the Su14 class would not have shown these types of effects.

Between-group analyses. Before examining the performance variables (i.e., quiz, exam, and final grades), it is important to note the extent to which the two classes differed on the questionnaires and demographic variables. On all questionnaires there were no significant differences between the groups with the exception of the *Motivation to Take the Class* questionnaire on the item that read "I couldn't get into another section of the course." This finding is unsurprising in that it is common for students to have trouble getting into a specific section of a course during the high enrollment demands of the normal academic semester. Enrollment demands are much greater in the fall semester compared to the summer session, which can force students into sections other than their primary choice (R. Rogers, personal communication, October 15, 2015). Although this finding is unsurprising, size of the mean difference ($d = 1.22$) between the two semesters is interesting. This finding also leads to another limitation to our design; it would have been better to use two classes from the same semester to account for nuisance variables like scheduling preferences and enrollment pressures. Summer courses at SJSU are less popular and more costly than are fall courses, which could result in differences in the types of students who would take summer courses such as those needing STAT 95 as a last-minute class to graduate, those who are more motivated to earn units, those who need the course as a prerequisite for fall classes, and/or those who have already taken and failed the class. Indeed, in our sample, compared to the fall students the summer students had more units and were more likely to have taken STAT 95 before. In addition, with

STAT 95 being the first level of statistics provided at SJSU and with one of the classes in this study being a fall semester, we were more likely to have incoming freshmen and lower-unit students. Results from the demographic questionnaire indicated that while the mean grade level for each class was ~3.00 (3.11 for all participants combined), when looking at each semester specifically, the Su14 class had mostly 4th year students and only one 1st year student while the Fa14 class had mostly 3rd year students and below. These group differences may have direct effects on how students scored on all variables, such that students with previous experience in statistics may be more predisposed to situational antecedents (i.e., attitudes towards statistics and prior knowledge; see Onwuegbuzie and Wilson, 2004). Gender composition may also be a concern with the present study as there are far more women than men. Gender difference findings are common among psychology research conducted at San José State University, in that most participants are women. As noted in Onwuegbuzie and Wilson (2004), gender differences are considered environmental antecedents, and previous findings show that women show higher levels of statistics anxiety. Since the Su14 class was found to have a higher percentage of females, it is important to consider that this may account for some of the variability in student performance. Overall and most importantly, the lack of significant differences and relatively small differences seen between the groups indicate that the groups were roughly similar. This helps clarify the effects of our self-management intervention, although we should note that the groups might differ on variables that we did not measures.

The primary goal of the study was to examine the effects of our self-management intervention on student performance. As seen in Table 10, the Fa14 class performed significantly better on two of the three performance variables (i.e., quiz grade and exam grade). Furthermore, the fact that there were no significant between-group differences in the covariate measures reduces the plausibility of these differences as explanations for the differences in course performance. This strengthens our inference that the between-group performance differences were due to the differences in course structure, particularly the self-management project. Of course, there are potential unmeasured nuisance variables that may account for these findings, but these findings suggest that incorporating a self-management project may improve course performance. Further research is needed to determine the extent to which such projects help students improve their course grades.

ABA design (within-group analysis). One aspect of the present study was the use of an ABA design in the Fa14 class. We wanted to know if delivering incentives in the form of participation points for asking and answering questions would increase the number of questions that students asked. We found that during the incentive period, students asked more questions compared to the first baseline, although the level-change coefficient was not significant (due to the upward trend in the first baseline phase). This upward trend in the first baseline phase likely reflected the fact that the course material became more complex and assignment due dates were approaching. More convincingly, we found that both the level change and slope change between the treatment (incentive) phase and last baseline phase were significantly different. Specifically, there was a significant decrease in the number of questions asked when we removed the incentives.

In addition, the upward trend in the treatment phase was replaced by a downward trend in the second baseline phase. We noticed that there were some students who did not participate in the asking/answering question period and other students who did every week. This tells us that either: (a) the non-responding students did not care for the three extra points a week because the 0.3% points toward their final grade was not strong enough positive reinforcement for these students; or (b) these students did not have any need to ask/answer questions. In fact, some students specifically stated in their final project that they did not have questions to ask, so they did not do so.

Although the points awarded were not extra credit points, it would be interesting to see if the results would have been different if they were extra credit points instead of weighted participation points. Furthermore, students may see more value in extra credit points because they are usually awarded rarely in university seminars, and with a course as difficult as statistics, extra credit might be more valued by most students. However, this does not necessarily mean that we would see change in behavior after the incentive is removed. As seen in Figure 1, a line of best fit depicts a gradual increase in questions asked per week in the Su14 class, whereas in the Fa14 class there is an obvious decline after the incentive is removed. Does this mean that the incentive actually had a negative impact on student participation? In a future study, it would be interesting to compare this design with another group where the incentive is present the entire semester and with one where there is no incentive. One major limitation in our ABA design is the strong possibility that students were unaware of the participation/incentive period. The incentive was communicated through the Piazza discussion board (the main source of communication between the instructor/statistics coaches and students). After the first week of the participation period, we noticed no change in the number of questions ask. To change this, we provided a reminder post about the incentive period. After the reminder, we began to see the sudden increase in questions asked. It is possible that there were too many posts in Piazza at once during the first announcement, and that students may have missed the announcement. We may have received better results if we would have personally emailed every student about the incentive period and/or had it added to the course syllabus.

Another recommendation for future research in this area interested in using incentives to encourage student participation is using an ABAB design. By adding a B' period we would leave the students with incentives for participation for the remainder of the semester. An ABAB design could also help us rule out the effects of some nuisance variables, which leads us to another limitation to our ABA design. Statistics courses are well known to start out relatively easy and have a steady increase in difficult as the course progresses. Using an ABA design, we noticed that at the beginning of the semester where we have no incentive and easier course material, we think that students may not have had any questions to ask. However, with our A' period being near the difficult period of the course, it is interesting that we did not see the positive behavior change. With an ABAB design, we could then see if having an incentive period near the difficult part of the course versus the easy part of the course differs on number of questions asked. An ABAB design would have provided more detailed information on how students behave and why.

Another limitation to our ABA design is how we divided up the ABA periods. Our first period where no incentive was present consisted of the first 3 weeks of the course. During this period students spent the first week completing student engagement activities in which they became familiar with the structure of the online course and their own preparedness for the course. Students did not see any statistics content during the first week of the course, so there was no need to ask statistics-related questions. During week 2 and 3 of the non-incentive period is where students first saw statistics-related content, so naturally the number of questions increased. The second period of the ABA design consisted of five weeks of statistics content. The final period consisted of nine weeks of content. It would have been beneficial to divide the periods up more evenly. This would allow us to have more precise data points throughout equal length periods. It could also diminish nuisance variables such as the lack of need to ask questions during the first period and content difficult of each period. Overall, our ABA design allowed us to see how incentives (participation points) could be used to change student behavior. We should note that students generally expressed dissatisfaction with the incentive system for asking questions.

Limitations

After seeing the lack of significant correlational evidence between our predictor (covariate) variables and our outcome variables, we believe that there may have been some limitations in our study. As described in the Introduction, previous research has been able to form links between the many constructs used in this study with academic performance in statistics-related classes. Why weren't all of these relationships found with the present study?

Sample size. Sample size was one of our main problems with the present study. Our total sample size was 38 participants (who answered the surveys) across both classes. The Su14 class had only 17 participants, and the Fa14 class had only 21 participants. For our overall outcome variable, we had access to *all* of the students enrolled in the course, allowing us to have a total sample size of 54 when looking at the outcome variables alone. Still, this is a small sample for detecting small-to-medium sized effects (Cohen, 1992). These differences in sample size might explain why we found significant differences when using the entire class versus the 38 participants. However, it is important to note that when comparing the participants' (who took surveys) performance variables, significant differences were found in that the Fa14 class performed better than the Su14 class. Although sample size did not have an effect on our outcome variables, it may be that it did have an effect on our correlation measures. Like the limitation to our ABA design, it might have been better if we individually emailed the students about taking the questionnaires and participating in the study to gain a larger sample size. Even if we did so, however, the class enrollment caps would prevent us from obtaining a large enough sample to detect relatively small effects. Of course, one could argue that small effects might not be of practical importance in this type of applied study. We would consider 5% points (about half a letter grade) as an "important" difference, but others may not agree.

Design. One major limitation to our design is the lack of post-class questionnaires. As stated above, it would have been extremely valuable to see how our covariate measures changed after the students experienced the courses. Using post-test analyses, we would be able to see any changes in attitudes towards statistics and self-reported self-regulation, self-management, and motivation. It would also allow us to further describe the groups both before and after the participants experienced the course. Future research should consider these options. Another limitation to our design is the use of a summer session and fall semester. As stated above, it may have been more beneficial to use two separate fall sections of the course. Although both of our classes had the same content, instructor, TAs, assignments, quizzes, and exams (with one extra in the Fa14 class), we have to understand that summer session courses attract different types of students than fall semesters. Although our data shows our groups are similar, there are greater chance of nuisance variables and confounds when using two different times of the year. The Su14 class was also much shorter (10 weeks vs. 16 weeks).

Nuisance variables. With the Su14 class being much shorter than the Fa14 class, we have to understand that a number of nuisance variables are clearly present. By having a shorter session, the course content approaches very rapidly. In the Su14 class, students were completing more content in a short period of time. This could cause more anxiety and resulted in poorer performance. Apart from anxiety, the shorter session meant that students had less time to study and reflect on the material, which also may have caused poorer performance. Another nuisance variable that may have been present was the enrollment cap of each class. The Su14 class had far less students than the Fa14 class allowing for fewer opportunities for communication between the students. This nuisance variable may have had an indirect effect on academic performance. This is another reason why it might have been better to use two class sections from the same semester.

Another nuisance variable is that the Su14 class had to learn to navigate two platforms (Canvas and Udacity), whereas the Fa14 class only had to navigate one platform (Canvas). It is possible that using two platforms increased cognitive load or time spent switching from one to another, and that variables associated with using two platforms influenced the performance of the Su14 students. It would have been interesting to see if students preferred using one platform versus two. As noted in the method, the Fa14 class was designed to more integrated and geared towards a simpler learning environment by having the problem sets from Udacity ported over to Canvas as quizzes. One nuisance variable to consider from this change is that some of the questions did not get ported over and administered in ways that Udacity had originally designed. Some questions required the Udacity platform and user interface that Canvas did not support. It is possible that the Fa14 class could have performed even better if they had a single platform that accommodated the pedagogical features of the Udacity platform.

Another possible nuisance variable is the fact that the Su14 students took proctored exams (using the ProctorU online proctoring service, www.proctoru.com). The Fa14 students did not take proctored exams. The use of the ProctorU service might have increased student test anxiety in the Su14 students. Additionally, the lack of face-to-face proctoring might have allowed students in the Fa14 class to use study aids (e.g., notes) that the Su14 students could not use. Although all Fa14 students made a pledge to not use study aids, we cannot guarantee that they did to do so. Lastly, by making both changes to the Fa14 class (i.e., adding self-reinforcement to the self-management project and administering the learning environment on one platform) it makes it harder to see which change (or both) had the effect on increased academic performance. All of these nuisance variables may have reduced our study's internal validity.

Conclusions and Future Direction

Overall, our data suggest that we did find something useful for professors teaching online statistics seminars. The use of a self-management project enabled students to work through the course with healthy behavior geared towards learning. Student performance was higher on all levels in the Fa14 class, with significant differences for quiz grade and exam grade. Future research in this area may want to look at other subjects instead of statistics. With statistics being a notably "high anxiety" college course, it would be interesting to see if students in a less anxious course value more or less from the self-management project. Also, by having future studies that use a similar design and methodology we could see how our findings compare to classes that have different lecture content, examination material, and the professor (e.g., would our design work with other teaching styles)? Future studies could also apply the self-management project to traditional in-person seminars/lectures or hybrid courses. It would be interesting to see how students in different settings benefit from similar projects as the one we used. One element that the present study lacked was an analysis of what the students used as self-reinforcement in the Fa14 class. Future studies could further investigate this to see if different types of reinforcement (e.g., social vs. activity reinforcers) work better than others. We could then make alterations to the self-management project that encourage students to use specific types of reinforcers to reduce their procrastination behavior. The current study has shown evidence that a self-management project might improve performance in an online statistics course. Future studies must now further this research area to continue to improve learning in online classes. Online education is only going to get more popular, so it is important for universities and colleges to continue to research techniques for improving student learning outcomes, including those that involve changing student self-regulation behavior. The availability of online courses make education more practical and accessible for students around the world. We owe it to our students to provide the most effective and supportive learning environments that we can, while helping them improve their own academic behavior.

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Appendix A

Demographic Questionnaire

Please answer the following questions about you and your background. Choose the answer that best describes you or enter the requested information.

1. What is your age? (In years) __________

2. What is your gender? (Choose one)

    1. Male

    2. Female

3. What is (are) your major(s)?

4. What is (are) your minor(s)?

5. What is your main college/university?

6. What is your college grade level? (Choose one.)

    1. Freshman

    2. Sophomore

    3. Junior

    4. Senior

    5. Post-baccalaureate

    6. Graduate student

    7. Other (please name): ____________________

7. What is your race/ethnicity? (Choose one)

    1. Hispanic, Latino, or Spanish

    2. White

    3. Asian (e.g., Asian Indian, Chinese, Filipino, Japanese, Korean, Vietnamese)

    4. Black/African American

    5. American Indian (North, Central, or South American) or Alaskan Native

    6. Native Hawaiian

7. Other Pacific Islander

8. Other (please name): ____________________

8. How many undergraduate units have you already completed? __________

9. How many undergraduate statistics and/or research methodology courses have you taken before this class?

10. How many math classes did you take in high school?

11. How many statistics classes did you take in high school?

12. How many psychology classes did you take in high school?

13. How many online classes have you taken before?

14. Are you taking this class for the first time or are you re-taking it to earn a better grade?

15. Have you applied for graduation yet?

Appendix B

Motivated Strategies for Learning Questionnaire (MSLQ)

For the following items, please indicate how well each statement describes you as a student **(where 1 = Not at all true of me; 3 = Somewhat true of me; 5 = Very true of me).** There are no right or wrong responses - only different ones. Please respond to all of the items.

1. I prefer class work that is challenging so I can learn new things.
2. Compared with other students in this class I expect to do well.
3. I am so nervous during a test that I cannot remember facts I have learned.
4. It is important for me to learn what is being taught in this class.
5. I like what I am learning in this class.
6. I'm certain I can understand the ideas taught in this course.
7. I think I will be able to use what I learn in this class in other classes.
8. I expect to do very well in this class.
9. Compared with others in this class, I think I'm a good student.
10. I often choose paper topics I will learn something from even if they require more work.
11. I am sure I can do an excellent job on the problems and tasks assigned for this class.
12. I have an uneasy, upset feeling when I take a test.
13. I think I will receive a good grade in this class.
14. Even when I do poorly on a test I try to learn from my mistakes.
15. I think that what I am learning in this class is useful for me to know.
16. My study skills are excellent compared with others in this class.
17. I think that what we are learning in this class is interesting.
18. Compared with other students in this class I think I know a great deal about the subject.
19. I know that I will be able to learn the material for this class.
20. I worry a great deal about tests.
21. Understanding this subject is important to me.
22. When I take a test I think about how poorly I am doing.
23. When I study for a test, I try to put together the information from class and from the book.
24. When I do homework, I try to remember what the teacher said in class so I can answer the questions correctly.
25. I ask myself questions to make sure I know the material I have been studying.
26. It is hard for me to decide what the main ideas are in what I read.
27. When work is hard I either give up or study only the easy parts.
28. When I study I put important ideas into my own words.
29. I always try to understand what the teacher is saying even if it doesn't make sense.
30. When I study for a test I try to remember as many facts as I can.
31. When studying, I copy my notes over to help me remember material.

32. I work on practice exercises and answer end of chapter questions even when I don't have to.
33. Even when study materials are dull and uninteresting, I keep working until I finish.
34. When I study for a test I practice saying the important facts over and over to myself.
35. Before I begin studying I think about the things I will need to do to learn.
36. I use what I have learned from old homework assignments and the textbook to do new assignments.
37. I often find that I have been reading for class but don't know what it is all about.
38. I find that when the teacher is talking I think of other things and don't really listen to what is being said.
39. When I am studying a topic, I try to make everything fit together.
40. When I'm reading I stop once in a while and go over what I have read.
41. When I read material for this class, I say the words over and over to myself to help me remember.
42. I outline the chapters in my book to help me study.
43.1 work hard to get a good grade even when I don't like a class.
44. When reading I try to connect the things I am reading about with what I already know.

Appendix C

Motivation to Take this Class Questionnaire

Please rate the importance of each of the following reason for taking this course. In other words, how important were each of these reasons in your decision to enroll in this course? **(1 = Not important; 3 = Moderately important; 5 = Very important)**.

1. I thought it would be fun and enjoyable.
2. The subject is relevant to my academic field of study
3. The class teaches skills that will help me in my job/career
4. I was curious to take an online course
5. The course is required for my major, minor, or degree program
6. The course fulfills General Education credit
7. I couldn’t get into another section of the course
8. I have an interest in the topic
9. I wanted to extend my knowledge of the topic
10. Other: please explain

Appendix D

Self-Control and Self-Management Scale (SCMS)

For the following items, please indicate how well each statement describes you **(where 1 = Not at all true of me; 3 = Somewhat true of me; 5 = Very true of me)**. There are no right or wrong responses - only different ones. Please respond to all of the items.

1. When I work toward something, it gets all my attention.
2. I keep focused on tasks I need to do even if I do not like them.
3. I become very aware of what I am doing when I am working towards a goal.
4. I make sure to track my progress regularly when I am working on a goal.
5. I pay close attention to my thoughts when I am working on something hard.
6. I know I can track my behavior when working toward a goal.
7. When I set important goals for myself, I usually do not achieve them.
8. I do not seem capable of making clear plans for most problems that come up in my life.
9. The goals I achieve do not mean much to me.
10. I have learned that it is useless to make plans.
11. The standards I set for myself are unclear and make it hard for me to judge how I am doing on a task.
12. I congratulate myself when I make some progress.
13. I get myself through hard things by planning to enjoy myself afterwards.
14. I silently praise myself even when others do not praise me.
15. When I do something right, I take time to enjoy the feeling.
16. I give myself something special when I make some progress.

Appendix E

Technology Use Questionnaire

Please answer the following questions about your use of various technologies, including computers and the Internet. Choose the answer that best describes you or enter the requested information.

1. Are you free to use a computer at work for non-work purposes (e.g., surfing the web, shopping online)
    a. Yes
    b. No
    c. Not applicable (either you don't work, or you don't have access to a computer at work)
2. Do you use the Internet at home?
    a. Yes
    b. No
3. Approximately how many years have you used the web?
4. Do you go online at least once per day?
    a. Yes
    b. No
5. On average, how many hours per day do you use the Internet?
6. Do you have high-speed Internet access at home?
    a. Yes
    b. No
7. Do you have a smart phone (e.g., iPhone, Android)?
    a. Yes
    b. No
8. If you do have a smartphone, do you use it to access the Internet (e.g., send email, surf the web)?
    a. Yes
    b. No
    c. Not applicable
9. Do you use the web to make purchases (e.g., on Amazon, iTunes store)?
    a. Yes
    b. No
10. Do you use the web for banking, to pay bills, or for other financial purposes?
    a. Yes
    b. No
11. Do you play online games?
    a. Yes
    b. No
12. Do you use social media sites (e.g., Facebook, Instagram, Pinterest)?
    a. Yes

b. No

13. Do you regularly use search engines (e.g., Google, Yahoo!)
    a. Yes
    b. No
14. Do you have regular access to a computer (laptop or desktop) at home?
    a. Yes
    b. No
15. About how many hours a day do you spend using a computer (laptop or desktop)?
16. Do you own a tablet computer (e.g., iPad, Kindle)?
    a. Yes
    b. No
17. In the past month, have you used the Internet to visit web sites for the following reasons (choose all that apply)?
    a. To read about national news
    b. To read about international news
    c. To read about sporting events or teams
    d. To read about political information
    e. To find health information
    f. To find financial information
    g. To learn about government services
    h. To learn product information
    i. To make an online purchase

Appendix F

Digital Literacy Questionnaire

How familiar are you with the following Internet-related items? Please choose a number between 1 and 5 that describes your level of understanding for each item. (1 = No understanding; 3 = Some understanding; 5 = Full understanding).

1. MP3 file
2. Preference setting on a web browser
3. Refresh/Reload on a web browser
4. Newsgroup
5. PDF file
6. Blog
7. Spam

Appendix G

Statistics Anxiety Rating Scale (STARS)

This is an inventory of your feelings toward statistics. There are no right or wrong responses - only different ones. You can indicate how much each statement describes your feelings by choosing the appropriate response below. If you don't understand the context the question is asking you, put down that it causes very much anxiety. **(1 = Causes me very little anxiety/agree and 5 = Causes me very much/disagree anxiety.** Please respond to all of the items.

1. Studying for an examination in a statistics course	1	2	3	4	5
2. Interpreting the meaning of a table in a Journal article	1	2	3	4	5
3. Going to ask my statistics teacher for individual help with material I am having difficulty understanding	1	2	3	4	5
4. Doing the homework for a statistics course.	1	2	3	4	5
5. Making an objective decision based on empirical data	1	2	3	4	5
6. Reading a journal article that includes some statistical analyses	1	2	3	4	5
7. Trying to decide which analysis is appropriate for your research project	1	2	3	4	5
8. Doing the final examination in a statistics course	1	2	3	4	5
9. Reading an advertisement for an automobile which includes figures on gas mileage, compliance with population regulations, etc.	1	2	3	4	5
10. Walking into the classroom to take a statistics test	1	2	3	4	5
11. Interpreting the meaning of a probability value once I have found it.	1	2	3	4	5
12. Arranging to have a body of data put into the computer.	1	2	3	4	5

13. Finding that another student in class got a different answer than you did to a statistical problem.	1	2	3	4	5
14. Figuring out whether to reject or retain the null hypothesis.	1	2	3	4	5
15. Waking up in the morning on the day of a statistics test	1	2	3	4	5
16. Asking one of your professors for help in understanding a printout	1	2	3	4	5
17. Trying to understand the odds in a lottery.	1	2	3	4	5
18. Seeing a student poring over the computer printouts related to his/her research.	1	2	3	4	5
19. Asking someone in the computer center for help in understanding a printout.	1	2	3	4	5
20. Trying to understand the statistical analyses described in the abstract of a journal article	1	2	3	4	5
21. Enrolling in a statistics course.	1	2	3	4	5
22. Going over a final examination in statistics after it has been graded.	1	2	3	4	5
23. Asking a fellow student for help in understanding a printout.	1	2	3	4	5

24. Since I am by nature a subjective person, the objectivity of statistics is inappropriate for me.	1	2	3	4	5
25. I haven't had math for a long time. I know I'll have problems getting through statistics.	1	2	3	4	5
26. I wonder why I have to do all these things in statistics when in actual life I'll never use them.	1	2	3	4	5
27. Statistics is worthless to me since it's empirical and my area of specialization is philosophical.	1	2	3	4	5

28. Statistics takes more time than it's worth.	1	2	3	4	5
29. I feel statistics is a waste.	1	2	3	4	5
30. Statistics teachers are so abstract they seem inhuman.	1	2	3	4	5
31. I can't even understand seventh- and eighth-grade math; how can I possibly do statistics.	1	2	3	4	5
32. Most statistics teachers are not human.	1	2	3	4	5
33. I lived this long without knowing statistics, why should I learn it now?	1	2	3	4	5
34. Since I've never enjoyed math, I don't see how I can enjoy statistics.	1	2	3	4	5
35. I don't want to learn to like statistics.	1	2	3	4	5
36. Statistics is for people, who have a natural leaning toward math.	1	2	3	4	5

37. Statistics is a grind, a pain I could do without.	1	2	3	4	5
38. I don't have enough brains to get through statistics.	1	2	3	4	5
39. I could enjoy statistics if it weren't so mathematical.	1	2	3	4	5
40. I wish the statistics requirement would be removed from my academic program.	1	2	3	4	5
41. I don't understand why someone in my field needs statistics	1	2	3	4	5
42. I don't see why I have to clutter up my head with statistics. It has no significance to my life work.	1	2	3	4	5
43. Statistics teachers talk a different language.	1	2	3	4	5
44. Statisticians are more number oriented than they are people oriented.	1	2	3	4	5

45. I can't tell you why, but I just don't like statistics.	1	2	3	4	5
46. Statistics teachers talk so fast you cannot logically follow them.	1	2	3	4	5
47. Statistical figures are not fit for human consumption.	1	2	3	4	5
48. Statistics isn't really bad. It's just too mathematical.	1	2	3	4	5
49. Affective skills are so important in my profession that I don't want to clutter my thinking with something as cognitive as statistics.	1	2	3	4	5
50. I'm never going to use statistics so why should I have to take it?	1	2	3	4	5
51. I'm too slow in my thinking to get through statistics.	1	2	3	4	5

Appendix H

Summer 2014 Self-Monitoring Project Guidelines

For this project, you are going to collect data on your own academic behavior with respect to this class. You should refer to your 10-week Schedule and Reflecting on Your Preparedness activities, as well as the number of videos per lesson information I posted. You will collect data from Week 2 and 3 (June 9-June 22). Be sure to use proper grammar, spelling, and punctuation in your submitted Project report. Use the posted Data Sheet Excel spreadsheet to record your data, compute your statistics, and create your graphs. Enter data into the white cells and obtain output from the green cells (do not enter any data into the green cells or change them). Enter 0 if you did not do any work that day. Round all values to two decimal places, even if the last two decimal places are zeroes.

Here is a list of tasks:

1. Set personal goals for the following variables (enter daily goals into the Data Sheet). If you do not plan on working on a given day, enter your goal as 0.

    a. **How many minutes you want to spend each day working on the course** (watching videos, completing Problem Sets, studying for exams, working on Projects, etc.)

    b. **How many Udacity videos you want to watch each day to have watched all videos by the due date** (see the list of number of videos per lesson to help you set this goal)

    c. **How many Problem Set questions you want to answer each day.** Although these are optional, they will provide excellent practice for the exams. I strongly recommend that you complete all Problem Set questions.

2. Record the following variables on a daily basis (it's best to do so right after you have completed the activity) using the Data Sheet Excel spreadsheet that I posted for you to use. Just replace the example data with your own.

    a. **Minutes spent each day** watching the Udacity videos or working on any aspect of the course, such as studying for an exam, working on a project, and so on. If it pertains to this course, count how long you worked on it.

    b. **Number of videos watched each day**. (Count re-watches as a separate "watch." For example, if you watched the same video twice, count that as a "2")

    c. **Number of Problem Set questions answered per day**.

d. **Whether or not you met your goal for that day (record 1 for "Yes" and 0 for "No")**

3. Using the example in the Data Sheet, create a line graph of:

   a. Raw data for Videos Per Day and Problem Set Questions Per Day.

   b. Cumulative data for Videos Per Day and Problem Set Questions Per Day.

4. For Week 2 and 3, identify the following descriptive statistics per week (these are computed for you in the Data Sheet):

   a. **Percentage of goals met** for those weeks for the three variables (% of goals met = number of days you met the goal/7 days).

   b. **Mean and Median** for the three variable listed above.

   c. **Standard deviation** for the three variables listed above.

5. After Week 2, reflect on how much time you have spent, etc. to see if you are on track. If you are not, create a plan to get on track for Week 3. Include this information in the paragraph describing your activities (explained in 7c below).

6. Create a table for the statistics from #4 (see example below).

7. Submit the following:

   a. **A table of descriptive statistics for the variables described above (see example below)**

   b. **Two line graphs for each of the three variables (see examples in the Data Sheet for Minutes Per Day)**

      i. Line graph 1: Raw data across weeks 2-3.

      ii. Line graph 2: Cumulative data across weeks 2-3

   c. **A written description of your goals and performance (in paragraph form):**

      i. A description of your goals for each day for Weeks 2 and 3.

ii. The total number of minutes spent across the two weeks working on the course (refer to your cumulative graph and the last value in the spreadsheet under the "Cumulative" column).

iii. Mean and median number of minutes spent each day for Weeks 2-3 and the standard deviation of those minutes (refer to your table)

iv. The total number of videos watched each week (refer to your cumulative graph and the last value in the spreadsheet under the "Cumulative" column).

v. Mean and median number of videos watched each day for Weeks 2-3 and the standard deviation of those videos (refer to your table)

vi. The total number of Problem Set questions answered each week (refer to your cumulative graph and the last value in the spreadsheet under the "Cumulative" column).

vii. Mean and median number of Problem Set questions answered each day for Weeks 2-3 and the standard deviation of those questions (refer to your table)

viii. Percentage of goals met for week 2 and 3 (refer to your table).

ix. Answer the following questions in your paragraph:

1. How did your actual data compare to your goals? How often did you meet your goals in each week?

2. Why did you or did not meet your goals in each week? What contributed to you meeting or not meeting your goals in each week?

3. If you did not meet your goals, what will you differently to make sure that you will meet your goals for the next Exam?

4. Did you see a change from Week 2 to Week 3? If so, what kind of change? What do you think contributed to this change?

5. Include the self-reflection information from #5 above.

6. Overall, what did this Project teach you about your ability to set goals and meet them? How will this Project change how you will approach the next several weeks?

Example table (you may copy and paste this same table; just replace the example data with your own):

Table 1. Data for Weeks 2 and 3

Variable	Mean	Median	*SD*	Percentage of Goals Met
Week 2				
Minutes Per Day	94.29	90.00	69.68	57.14
Videos Per Day	8.86	10.00	2.04	71.43
Problem Set Questions Per Day	11.71	12.00	3.15	71.43
Week 3				
Minutes Per Day	108.57	120.00	73.07	85.71
Videos Per Day	12.29	13.00	2.69	85.71
Problem Set Questions Per Day	12.71	15.00	3.59	57.14

Appendix I

Fall 2014 Self-Management Project Guidelines

Please read the Malott & Harrison (*I'll Stop Procrastinating When I Get Around To It*) chapters posted on Canvas (read in this order: Ch. 10, 9, 3). Be sure to read all of the examples to see the various ways you can create your self-management project. Remember that your target behavior is working on Stat 95 (defined as watching videos, taking notes, studying for exams, working on this project, asking and answering questions, taking quizzes, completing problem sets, etc.) and your dependent variable is the number of minutes per day spent working on this class (feel free to add more specific variables like number of videos watched per day, etc.). Please follow these guidelines when writing your proposal. Your proposal may be in outline form, but please use complete sentences and proper grammar, spelling, and punctuation. If you like, you may type your answers under each item below. Feel free to add any additional details as you see fit. Submit the completed proposal (in doc, docx, or pdf format) to the Canvas drop box by the stated due date in Canvas.

1. **Analyze the problem**.

    a. Specify the ineffective natural contingency. In other words, why aren't you doing what you want to do?

        i. What are the consequences that should, but may not, influence your studying behavior in the right direction, such as keeping it at appropriate levels of increasing it to necessary levels to succeed in this course?

        ii. What antecedents are not in place to support your working on this class? In other words, what environmental events may not properly "set you up" for success when trying to study?

    b. Specify the natural effective competing contingency.

        i. What are the consequences that might keep you from behaving how you want to?
            1. Alternative incentives, which are things you would rather be doing than working on this class. (examples below)
                a. Spending time with friends, loved ones, family
                b. Spending time on fun activities
            2. Aversives related to working on this class. (examples below)
                a. It's effortful

        b. It's boring
        c. It takes time from other, more enjoyable activities
    3. Others?

ii. What antecedents are in place that might work against your studying behavior? In other words, what environmental events might "set you up" for not studying? (examples below)
    1. Presence of friends.
    2. Presence of your smart phone.
    3. Other, more attractive, web sites open (e.g., Facebook)

2. **Specify your goal(s)**. Be sure that your goal(s) are quantifiable, clear, and easy-to-measure.

    a. When will you work on this class? How often, on what days, and for how long?

    b. Be sure that your goals are not too large or ambitious to meet realistically

3. **Design your measurement system**.

    a. When will you collect data?

    b. How will you collect data? Note that eventually you will put the data into the Excel spreadsheet provided to you on Canvas. If you plan on just using the spreadsheet, just indicate this.

    c. How often will you collect data? Ideally, you will collect data every day, right after you are done working on the class.

4. **Design your intervention (implement your intervention immediately & start recording data).**

    a. List any incentives and/or aversives you will use to change your behavior. Remember, they should be relatively sizable, immediate, frequent, and probable. What good (and/or bad things) happen when you meet your goal?

    b. List environmental changes you will make to "set you up for success." What will you do to your surroundings to support your academic behavior?

    c. State deadlines for performing your behavior and what happens if you do or don't meet your goal. When must you meet your goal for the incentive to be delivered and/or when is the aversive delivered for not meeting your goal?

5. State your criteria for recycling your intervention.

a. What data will tell you that your intervention is not working?

b. How long will you try out your current intervention before you recycle it?