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COLLEGE STUDENTS' SELF-REGULATION IN ASYNCHRONOUS ONLINE COURSES DURING COVID-19: A CONVERGENT MIXED METHODS APPROACH

Jaeyun Han
University of Kentucky, jyhan1610@gmail.com
Author ORCID Identifier:
https://orcid.org/0000-0002-2009-7191
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Jaeyun Han, Student

Dr. Ellen L. Usher, Major Professor

Sharon S. Rostosky, Director of Graduate Studies

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DISSERTATION

A dissertation submitted in partial fulfillment of the
requirements for the degree of Doctor of Philosophy in the
College of Education
at the University of Kentucky

By

Jaeyun Han

Lexington, Kentucky

Co-Directors: Dr. Ellen L. Usher, Professor of Educational Psychology

and Dr. Daniela K. DiGiacomo, Assistant Professor of School of Information Science

Lexington, Kentucky

2022

https://orcid.org/0000-0002-2009-7191

ABSTRACT OF DISSERTATION

COLLEGE STUDENTS' SELF-REGULATION IN ASYNCHRONOUS ONLINE COURSES DURING COVID-19: A CONVERGENT MIXED METHODS APPROACH

The purpose of this dissertation study was to use a convergent mixed methods approach to understand college students' self-regulation in asynchronous online courses in Fall 2020. Since the start of the COVID-19 pandemic, asynchronous online modalities have been more broadly utilized in higher education. Although undergraduate students can have greater flexibility in how they engage with their courses, students may regulate their learning differently when facing a web-based instructional modality, which may affect their academic performance. According to Bandura's social cognitive theory, students' beliefs in their self-regulatory capabilities are interdependent with self-regulatory behaviors. In particular, academic procrastination has been often observed in college students even though they are expected to be more self-regulated and independent learners. Rarely have researchers sought to examine the bidirectional relationship between self-efficacy for self-regulated learning and procrastination behaviors and its impacts on course performance. Little is also known about students' perceived challenges in asynchronous online courses in conjunction with their levels of self-efficacy for self-regulated learning and procrastination behaviors. The following research questions guided the investigation of this dissertation: (1) What is the relationship between students' self-efficacy for self-regulated learning, academic procrastination, and course performance? (2) What do students report as the most challenging aspect(s) of their asynchronous online courses? and (3) What are the major challenges experienced by students with low and high levels of self-efficacy for self-regulated learning and academic procrastination? Undergraduate students (N = 1,216; 74.7% White, 69.3% female) attending a public U.S. university were surveyed at two time points (Time 1: September, Time 2: November) in Fall 2020. Students were enrolled in 1 of 35 participating course sections taught in an online, fully asynchronous modality. Students' self-efficacy for self-regulated learning and academic procrastination were assessed via self-report rating scales. Students' self-rated performance and their final course grades were outcomes of interest. An open-ended question prompted students to describe the biggest challenge(s) they had experienced in their asynchronous online courses. A cross-lagged panel model revealed that students with higher self-efficacy for self-regulated learning at Time 1 tended to have lower academic procrastination at Time 2, which resulted in more desirable course performance. However, students who reported high academic procrastination at Time 1 tended to have lower self-efficacy for self-regulated learning at Time 2, which resulted in less desirable course performance. Inductive coding of students' open-ended responses revealed that time management was perceived as the most challenging aspect of asynchronous online learning at both time points. Students with higher self-efficacy for self-regulated learning and those with lower academic procrastination were more likely to indicate that they did not experience any challenges. The findings highlight the ways in which students' beliefs in their self-regulatory capabilities and procrastination behaviors are related to each other and differently contribute to course performance. This study has theoretical and practical implications for timely support of college students' self-regulation in asynchronous online learning courses during and after COVID-19.

KEYWORDS: Self-Efficacy for Self-Regulation, Academic Procrastination, Performance, Asynchronous Online Learning, Higher Education

Jaeyun Han
(Name of Student)

12/6/2022
Date

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Sharon S. Rostosky
Director of Graduate Studies

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CHAPTER 1. INTRODUCTION

Among the most important factors related to academic success is the ability to execute effective strategies to progress towards one's goals, or *self-regulation* (Bandura, 1991). Implementing self-regulatory strategies, such as staying focused in lectures or practicing time management skills, is crucial for learning (Zimmerman & Martinez-Pons, 1986). Although self-regulatory skills are important for learning and achievement, not all students regulate their cognition, behaviors, and emotions well. For example, some might procrastinate, or delay their schoolwork, despite knowing that doing so will not benefit them in the long term (Steel, 2007). Students may be particularly likely to postpone their coursework if they doubt that they can successfully employ self-regulatory strategies to manage it (Schunk & Zimmerman, 2008).

Identifying ways to support college students' motivation and behaviors for self-regulated learning has been a focus of researchers for some time (Cassidy, 2011). In particular, new attention to self-regulatory processes has emerged since the onset of the COVID-19 pandemic, which brought a dramatic shift from traditional face-to-face instruction to fully online learning environments (Hensley et al., 2022). There has long been evidence to suggest that students may need better self-regulatory skills during sensitive periods such as transitions to new educational environments (Schunk, 2005; Zimmerman, 1990). This dissertation study focuses on college students, many of whom are expected to become more independent learners in their university environment. Of note, this dissertation is also embedded within a moment of disruption due to a global pandemic that changed the way many courses were delivered.

Asynchronous online learning has been one of the major instructional delivery formats during COVID-19 (Camilleri & Camilleri, 2021). According to the National Center for Education Statistics (2021), 75% of undergraduate students from the 50 states and the District of Columbia enrolled in at least one synchronous or asynchronous online course in fall 2020. The rapid advance in asynchronous online learning technologies has provided students with greater flexibility for engagement in their courses. However, for many students, the shift from in-person to remote instruction introduced new challenges to learning. Many students who were enrolled in web-based courses that lacked externally-imposed accountability structures (e.g., consistent check-ins or required meeting times) reported decreased motivation and increased difficulty managing their work (e.g., Usher et al., 2021).

Students' beliefs about their capabilities have been emphasized as an essential component of their academic success in college (Richardson et al., 2012). When students face challenging tasks, they may re-evaluate their capabilities (i.e., "Can I do this?"). The more strongly students believe in their capabilities to manage their learning, the more likely they are to execute adaptive self-regulatory skills (Usher & Schunk, 2018). In college, academic procrastination has been observed as a behavioral sign of students' poor self-regulation, as it indicates a failure to manage one's time effectively (Wolters & Brady, 2021). Less is known about how personal efficacy beliefs might be associated with the tendency to procrastinate and vice versa, particularly in asynchronous online courses. In addition, rarely have researchers examining self-regulatory beliefs and behaviors in asynchronous online learning environments integrated students' voices about their challenges. Understanding what kinds of difficulties students experienced in this unique learning context could also help shed light on the role of self-efficacy for self-regulation and procrastination behaviors in affecting undergraduate students' learning during the pandemic.

Statement of the Problem

Previous studies have suggested that students who feel more confident in their capability to regulate their learning are better able to use and adapt to online learning systems (e.g., Cui, 2021). On the other hand, students who doubt their own self-regulatory capabilities may be more likely to delay their academic work (e.g., Klassen et al., 2008). Students may also reassess their personal capability beliefs according to where and when they need to exercise self-regulatory skills. Most previous research has examined these factors—self-efficacy for self-regulated learning and academic procrastination—at one time point and mostly in traditional or face-to-face learning environments, which may limit the ability to understand how they influence each other over time in various learning contexts.

According to Bandura's (1997) social cognitive theory, personal beliefs and behaviors are interdependent; each can influence the other. Although researchers have shown that learners' self-efficacy is related to their academic behaviors, rarely have they examined whether students' self-regulatory behaviors, such as procrastination, are important factors that affect students' beliefs about their capabilities to manage their learning effectively. A documented predictive relationship between self-regulation behaviors and self-efficacy would potentially inform educational interventions that help improve self-regulation skills (Usher & Pajares, 2008). However, more studies are needed to comprehend the nuanced experiences of students' web-based learning in the time of COVID-19 as it relates to self-efficacy for self-regulated learning and academic procrastination. Investigating the mutual relationships between students' personal beliefs and behaviors for self-regulation can also broaden the current understanding of possible mechanisms explaining why some students achieve better learning outcomes than others.

This study employs a convergent mixed methods approach that allows for a triangulation of qualitative and quantitative analytic findings (Creswell & Plano Clark, 2017). As Nolen (2020) emphasized, "the range of research methodologies and methods has never been broader, the issues at stake in education have never been more important, and the complexity of the phenomena and contexts we study has never been more apparent" (p. 271). The quantitative investigation of this study adds to the literature by examining the possible bidirectional relationship between self-efficacy for self-regulated learning and procrastination and their ultimate impacts on outcomes in the context of asynchronous online learning. The qualitative investigation also discloses the underlying challenges college students faced when learning fully asynchronously during the early months of COVID-19. Furthermore, examining students' qualitative descriptions of their primary learning challenges in asynchronous online courses by levels of their self-regulatory beliefs and behaviors could help researchers and practitioners understand the types of supports based on modality.

Purpose of the Study

The overarching goal of this study was to empirically investigate undergraduate students' self-regulation in asynchronous online courses during COVID-19. Using convergent mixed methods, this study focused on undergraduate students' self-regulatory beliefs, behaviors, and perceived challenges in asynchronous online courses during Fall

2020. The specific aims of this dissertation study were: (1) to examine associations between students' self-efficacy for self-regulated learning, procrastination behaviors, and self-rated performance and final course grades; (2) to explore students' reflections on their greatest challenges to learning in their asynchronous courses; and (3) to investigate differences in students' perceived challenges according to their levels of self-efficacy for self-regulated learning and academic procrastination. This dissertation study can provide insight into the motivational and behavioral aspects of self-regulation in relation to academic success in asynchronous online courses, which is informative for educators who aim to support their undergraduate students' self-regulated learning during and after COVID-19.

CHAPTER 2. REVIEW OF THE LITERATURE

I begin this chapter by providing an overview of social cognitive theory (Bandura, 1997) as the guiding theoretical framework for this investigation. I then review previous studies examining the relationship between self-efficacy for self-regulated learning, academic procrastination, and performance as well as student-reported challenges in the context of asynchronous online learning in college.

Theoretical Framework

Bandura's (1997) social cognitive theory posits reciprocal influences between the personal, behavioral, and environmental factors that affect learning. Compared to other theories assuming a one-sided impact of the environment on the learner, social cognitive theory postulates that "people are producers as well as products of their social environment" (Bandura, 2004, p. 76). In confronting an imposed environmental change, students can initiate strategies to help manage their motivation and behaviors (Pajares, 1996; Schunk & Usher, 2012). In the absence or limited availability of in-person learning options during the first wave of the COVID-19 pandemic, self-regulation, or "self-generated thoughts, affects, and behaviors that are systematically oriented toward attainment of one's goals" (Schunk & DiBenedetto, 2020, p. 5) became increasingly important to students' success.

A model of self-regulated learning put forth by Zimmerman and his colleagues shows that integral self-regulatory processes take place before, during, and after a learning event (e.g., Zimmerman & Campillo, 2003; Zimmerman & Moylan, 2009). Their self-regulation model is situated within a broader social cognitive theoretical framework, which assumes that human capacities enable learners to exercise some degree of agency over their own learning (Zimmerman, 1989). Students' self-regulated learning jointly involves motivational, behavioral, and self-reflection phases. Given that self-regulated learners show "proactive efforts to seek out and profit from learning activities," they are more likely to earn higher grades and to demonstrate favorable behavioral strategies in learning (Zimmerman, 1990, p. 6).

Students' beliefs in their personal capabilities are powerful motivators for academic functioning. Students may hold certain beliefs about whether they can manage their motivation, attention, behaviors, emotions, and other resources for effective learning. This collective set of beliefs is called *self-efficacy for self-regulated learning*. Personal efficacy beliefs can lead to more adaptive behaviors because "people who have a tenacious belief in their capabilities will persevere in their efforts despite innumerable difficulties and obstacles" (Bandura, 1997, p. 43). Therefore, students who have a high sense of self-efficacy for self-regulation tend to show effective task management skills such as planning ahead and completing assignments on time, which can lead to better academic performance (Zimmerman et al., 1992).

Bandura (1997) emphasized that personal beliefs and behaviors are interconnected, and it may take time for one to impact the other. Although personal capability beliefs are important for subsequent behaviors, academic procrastination can also bring about changes in individuals' self-efficacy for self-regulated learning. It is plausible that students who have delayed their coursework may later feel less confident in their capabilities to self-regulate their learning than those who have managed their coursework in a timely manner. In addition, students can have different learning experiences in given environment according to their self-regulatory strategies (Zimmerman, 2002).

Impacts of Self-Regulatory Beliefs on Procrastination and Performance

Self-efficacy for self-regulated learning has been operationalized as confidence in one's ability to carry out self-regulatory tasks needed for productive learning. In his guide to measuring self-efficacy, Bandura (2006) provided a scale to assess individuals' self-efficacy for self-regulated learning by asking them to rate their degree of confidence that they could perform self-regulatory tasks such as finishing homework assignment by deadlines and organizing their schoolwork. Although self-regulatory skills are important for academic achievement, not all students believe that they can regulate their learning well. In particular, the college setting often presents students with academic challenges that require a greater degree of self-regulation than may have been necessary during high school (Pintrich, 2004). This may be because external supports for self-regulation (e.g., parents, teachers) are less readily available, and students need to be more responsible for managing their learning in college.

Previous studies have found that students' self-efficacy for self-regulated learning is an important correlate of their self-regulatory behaviors such as academic procrastination and performance in college. For example, Haycock et al. (1998) found that college students with higher self-efficacy for completing projects by a specific deadline were less likely to procrastinate than were students with lower self-efficacy. Klassen et al. (2008) similarly found that undergraduate students who had higher self-efficacy for self-regulated learning were less likely to procrastinate in their academic work than were those who doubted their capabilities to manage their learning. In a crosscultural examination of undergraduate students' motivation and academic procrastination in Canada (n = 192) and Singapore (n = 226), researchers also found that students with higher self-efficacy for self-regulated learning were less likely to procrastinate on academic tasks (Klassen et al., 2010).

Few studies have longitudinally examined undergraduate students' self-efficacy for self-regulated learning and academic procrastination. Yerdelen et al. (2016) investigated 182 Canadian undergraduate students' academic procrastination in relation to their initial levels of self-efficacy for self-regulated learning at four time points, each at two-week intervals, during one semester. Overall, students' academic procrastination increased over time. In addition, students who had higher self-efficacy for self-regulated learning were more likely to report lower levels of academic procrastination at the beginning of the semester.

Some researchers have included achievement outcome measures in their investigation of the impact of students' self-regulatory beliefs on academic procrastination. For example, Tan et al. (2008) found that, among undergraduate students, those with lower self-efficacy for self-regulated learning were more likely to procrastinate on their tasks and to expect poor achievement at the end of the academic year than were those with higher self-efficacy for self-regulated learning. However, less is known about indirect relationships among these variables measured at different time points, such as whether low self-regulatory self-efficacy at the beginning of semester may have negative effects on final academic achievement by leading to certain problematic self-regulatory behaviors like academic procrastination during the class.

Impacts of Procrastination on Self-Regulatory Beliefs and Performance

The literature reviewed above suggests that beliefs about one's self-regulatory capabilities are important motivational antecedents of academic procrastination. However, findings are inconclusive regarding the effects of academic procrastination on subsequent self-efficacy for self-regulated learning. Students who tend to procrastinate in their coursework may later reflect on their behavior and conclude that they are not good at self-regulated learning. In this section, I review how academic procrastination has been examined as a predictor of self-efficacy for self-regulated learning.

From the perspectives and practices of self-regulated learners, procrastination has been considered as "the lack or absence of self-regulated performance" (Tuckman, 1991, p. 474). Students' procrastination tendencies have been found across various tasks or broad situations such as schoolwork, phone call response time, or decision making (e.g., Lay, 1986). Researchers have also specifically focused on examining procrastination on academic tasks (i.e., academic procrastination), which is frequently observed among university students (Steel, 2007). Overall, evidence suggests that students' tendencies to postpone academic work are closely related to a lack of self-regulatory skills and poor performance in higher education (Schneider & Preckel, 2017).

Although procrastination has primarily been viewed as an outcome of personal capability beliefs, several researchers have examined procrastination as a precedent of self-efficacy for self-regulation. For instance, Sirois (2004) proposed that general procrastination (e.g., "I am continually saying I'll do it tomorrow") would have both direct negative impacts on undergraduate students' intention to engage in healthy behaviors and indirect negative impacts on it by decreasing students' self-efficacy for managing their health (e.g., “I am confident that I can successfully look after my health”). Indeed, the researchers found that students with higher levels of procrastination tended to have lower self-efficacy for managing their health than did those with lower levels of procrastination.

Researchers have similarly found a negative relationship between academic procrastination and students’ achievement or achievement expectations (Kim & Seo, 2015). Undergraduate students who reported higher levels of academic procrastination tended to expect low grades in the courses they were taking, even when other motivational and behavioral variables were controlled for (Wolters & Hussain, 2015). Klassen et al. (2010) examined how students might perceive their decision to procrastinate. They classified students as negative procrastinators and neutral procrastinators based on their responses to the question, “In general, how much does procrastination negatively influence your academic functioning?” Undergraduate students who were classified as negative procrastinators tended to have lower self-reported course GPAs than did those classified as neutral procrastinators.

A handful of studies have examined the indirect impact of procrastination on achievement through its influence on other variables, such as self-efficacy. For example, Kennedy and Tuckman (2013) found that procrastination at the beginning of the semester had negative indirect effects on undergraduate students’ GPA at the end of the semester by lowering levels of self-efficacy for self-regulated learning. The multiwave design of the study was useful for examining causal relationships from procrastination to subsequent beliefs. However, these findings may be still limited without considering the possible impact of self-regulatory beliefs on procrastination behaviors.

Drawbacks of Asynchronous Online Modalities

To lower the risk of transmission of COVID-19 during traditional in-person meetings, many universities moved to online learning formats during the early months of the pandemic. Studies that were focused on undergraduate students' learning experiences during the initial outbreak of COVID-19 indicated a need for more research on the specific self-regulatory challenges students might have experienced while learning during the pandemic, often in new online learning formats (Usher et al., 2021). Even under non-pandemic circumstances, the college setting itself may present students with academic challenges that require a greater degree of self-regulation to optimize their resources (Bembenutty, 2011).

Recent qualitative investigations indicate that students might tend to perceive difficulties or additional burden of regulating their online learning during a global pandemic. For instance, Hensley et al. (2022) conducted a qualitative study to examine college students' perceptions about the drastic shift to online learning in Spring 2020. Broad thematic analyses of six open-ended questions (e.g., "How was your motivation for your academic courses impacted by the changes that resulted from the coronavirus [COVID-19) pandemic?") revealed that students primarily struggled with online learning during the semester and described decreased motivation and engagement in their online courses as well as increased workload and emotional stress.

Students' procrastination has been identified as a barrier to effective online learning during COVID-19. Hong et al. (2021) quantitatively examined the online learning experiences of Chinese undergraduate and graduate students during the pandemic. Students who procrastinated on their work tended to report a lack of proactive time management such as allocating extra study time in advance for their demanding online courses. In addition, students with higher levels of academic procrastination were less likely to manage their learning through environmental restructuring such as relocating themselves to quiet spaces to participate in their online courses. The findings suggest that procrastinators may be more likely to experience challenges in their online learning.

Much of the previous research in online learning contexts has not accounted for various online modalities but rather has broadly classified “online” instruction as that which does not take place in physical classroom spaces (Picciano, 2006). Although researchers have broadly examined students’ experiences in their “online” courses, most have not considered differences by instructional delivery format. Students enrolled in courses taught synchronously using video conferencing platforms typically have scheduled days and times for class meetings with their instructor and other students. By contrast, in fully asynchronous online courses, most students’ learning experiences are processed and evaluated within web-based learning management systems. Such courses tend to require more self-regulation with more flexibility for course participation (e.g., recorded lectures might be available for students to watch at their leisure; Bernard et al., 2004).

Some empirical evidence suggests that learners disengage or lack diligence in their asynchronous online lectures when more flexibility is given. For example, in voluntary asynchronous online learning programs with less strict date requirements such as Massive Open Online Courses (MOOCs), many learners experience self-regulatory challenges and show discontinuous course engagement (Reich & Ruipérez-Valiente, 2019; Rivers et al., 2022). Compared to MOOCs, asynchronous online courses in college are at least officially bound within a semester and linked to the institution's official evaluation system for academic records. Thus, there is an empirical need to examine what kinds of challenges students may experience in college courses that are offered only in online, asynchronous modalities.

Purpose of the Study and Research Questions

During the COVID-19 pandemic, instructional modalities have become more diversified, and students have shown individual differences in self-regulated learning and performance. Academic procrastination is often observed among college students, and previous research has often unidirectionally examined it as an outcome of low beliefs in one's self-regulated learning. Less is known about the interdependence of personal self-regulatory beliefs and behaviors in asynchronous online courses in college. Moreover, the challenges students experience might depend on students' self-regulatory beliefs and behaviors. Using convergent mixed methods, the current study therefore aimed to investigate the reciprocity and effects of self-efficacy for self-regulation and academic procrastination with emerging challenges in asynchronous online courses during COVID-19. The following research questions guided the investigation:

RQ1: What is the relationship between students' self-efficacy for self-regulated learning, academic procrastination, and course performance?

RQ2: What do students report as the most challenging aspect(s) of their asynchronous online courses?

RQ3: What are the major challenges experienced by students with low and high levels of self-efficacy for self-regulated learning and academic procrastination?

CHAPTER 3. METHOD

Study Design

This study used a convergent mixed methods design to comprehensively understand undergraduate students' learning experiences in their asynchronous online courses during Fall 2020. A convergent mixed methods design helps "to bring together the results of the quantitative and the qualitative data analysis so that they can be compared or combined" (Creswell & Plano Clark, 2017, p. 65). A hypothesized path model was analyzed using quantitative data to examine which measured variables are associated with each other and significantly related to students' self-rated performance and actual final course grades. An open-ended question was used to solicit students' perspectives about the most challenging aspect of learning in their asynchronous online courses. Students' responses were thematically analyzed and then integrated with the quantitative data for a richer understanding of the challenges experienced by students who reported different levels of self-efficacy for self-regulated learning and academic procrastination.

Participants and Procedures

This study was part of a larger investigation of undergraduate teaching and learning during the fall 2020 semester at a public, land-grant university in the southeastern United States. In the summer of 2020, the research team began discussing how to implement a timely survey to capture students' course-specific academic motivation and engagement in the early months of the COVID-19 pandemic. The university's Institutional Review Board approved the project. Students were invited to complete online surveys assessing their course-related beliefs and behaviors at two time points during the fall semester of 2020 (Time 1: September, Time 2: November). Recruitment occurred via communications with administrators (e.g., department chairs) and through direct outreach to instructors. Only students whose instructors volunteered to participate in the project were invited to take part. The full sample consisted of 6,060 students who took part at Time 1 and 5,835 students who took part at Time 2. Students who were enrolled in more than one participating course section were invited to participate in surveys for each course.

The current study focused only on students who were enrolled in fully asynchronous online courses as reported by the university's classification for web-based distance learning and the description of the course provided by the instructor. The study sample included 1,216 undergraduate students enrolled in 35 course sections across a broad range of disciplines in the humanities, social sciences, natural sciences, and business. The course sections were taught by 21 instructors, 57% of whom had more than one year of online teaching experiences. According to University records, students in the sample were 74.7% White, 7.2% Black, 5.3% Hispanic, 3.0% Asian, 3.7% multiracial, 0.2% Native Hawaiian or other Pacific Islander, 0.2% American Indian or Alaskan Native, and 5.8% from unknown racial/ethnic background. The university identified gender as a binary variable from which participants were categorized as 69.3% female and 30.5% male (0.2% missing). Students' academic year level was categorized in five ways: 20.0% of students were in their first year, 17.3% were sophomores, 31.7% were juniors, 30.0% were seniors, and 1.0% were non-degree seeking. University records also indicated that 27.0% of students were first-generation college students whose parents or guardians did not earn a bachelor's degree. This demographic composition approximately paralleled that of the full campus of undergraduate students enrolled in Fall 2020 (i.e., 74.9% White, 7.1% Black, 5.6% Hispanic, 3.1% Asian, 4.0% multiracial, 0.1% Native Hawaiian or other Pacific Islander, 0.2% American Indian or Alaskan Native, and 5.1% unknown racial/ethnic background; 56.7% female, 43.3% male; 23.6% in first year, 22.4% sophomores, 23.7% juniors, 30.1% seniors; 27.6% first generation, 72.4% continuing generation).

Measures

Self-efficacy for self-regulated learning was measured using six items adapted from Bandura's (2006) scale. A subset of items was selected to minimize the response burden on students and to reflect likely self-regulatory skills needed in successful online learning. The specific items were, "I can meet assignment deadlines for this class," "I can concentrate on my work for this class," "I can remember information presented in this class," "I can arrange a place to study for this class without distraction," "I can motivate myself to do my work in this class," and "I can manage my stress related to this class." Students responded on a 6-point scale, from 1 (*strongly disagree*) to 6 (*strongly agree*). The coefficient alpha values were .89 at Time 1 and .90 at Time 2.

Academic procrastination was assessed using a 2-item scale adapted from Lay's (1986) procrastination scale. The specific items were, "I generally delay before starting on work for this class" and "I usually have to rush to complete tasks for this class on time." Responses were recorded on a 6-point scale, from 1 (*strongly disagree*) to 6 (*strongly agree*). The coefficient alpha values were .71 at Time 1 and .78 at Time 2.

Students were also asked at Time 2 to evaluate their own performance in the course (i.e., "How would you rate your overall performance in [Course] this semester?")

on a 5-point scale, 0 (*terrible*), 1 (*poor*), 2 (*fair*), 3 (*good*), and 4 (*excellent*). The distal achievement outcome of interest was students' course grade, which was obtained from university records and classified as 0 (F), 1 (D), 2 (C), 3 (B), and 4 (A). A higher score indicates better achievement.

For statistical control purposes, a prior achievement variable was collected from university records in the form of students' unweighted high school GPAs, which ranged from 1.6 to 4.0. Although other control variables may be important to examine, limitations to the modeling approach described below prevented me from including them.

Perceived challenges in the course were assessed with the open-ended question, "What has been the most challenging part of [Course] so far?" at Time 1 and "What has been the most challenging part of [Course]?" at Time 2. No word limit was imposed, and students could freely skip the question if desired.

Analytical Approach

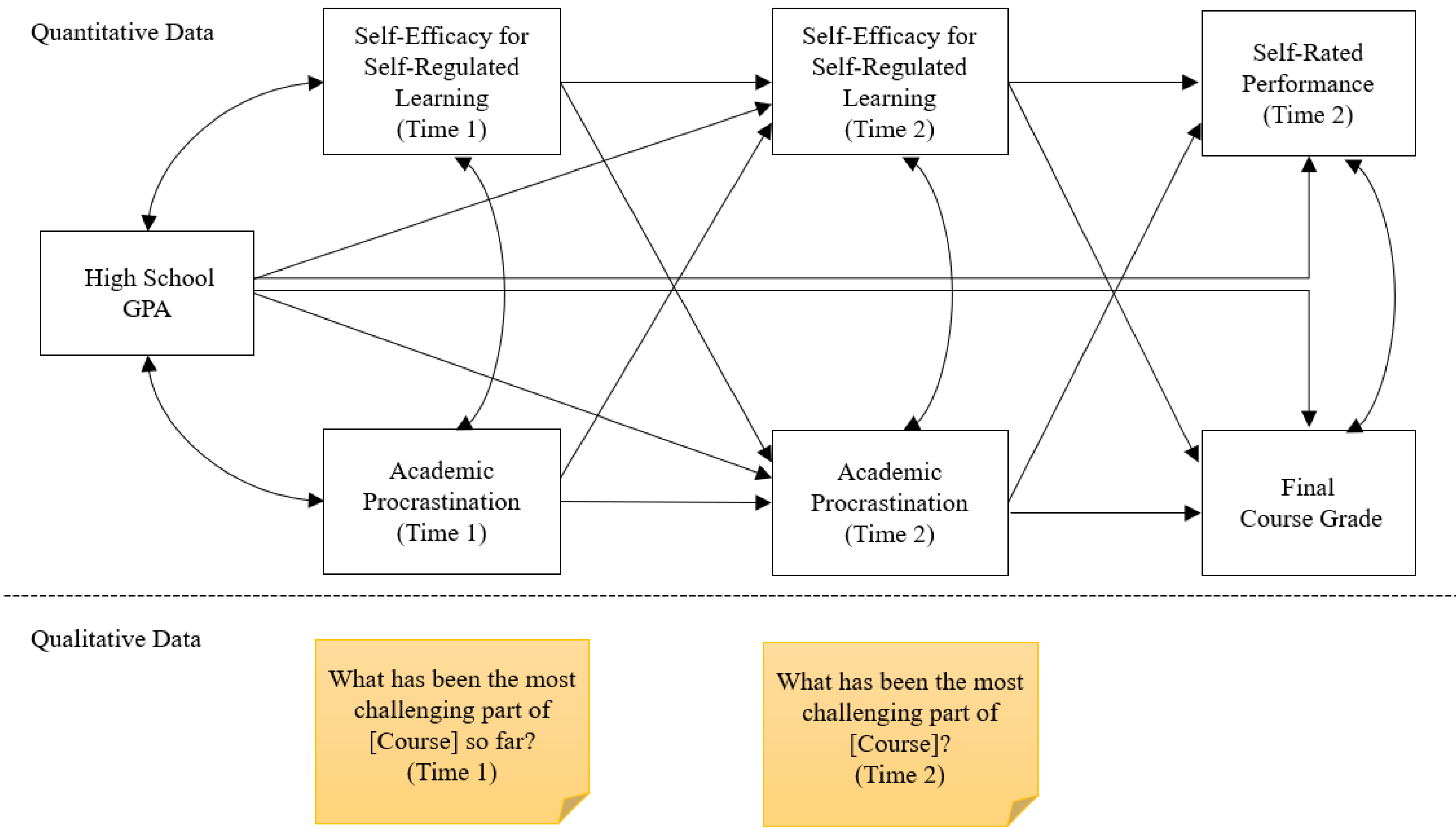
Mplus 8.8 was used to conduct quantitative data analyses (Muthén & Muthén, 2022). As a basic step, descriptive statistics and correlation analyses were calculated for each variable. A closer examination of the patterns of missingness was also conducted. Missingness in self-efficacy for self-regulated learning, academic procrastination, and self-rated performance measured at Time 2 was negatively related to high school GPA (r = -.12, p < .001) but was not significantly associated with the observed scores of self-efficacy for self-regulated learning and academic procrastination at Time 1. Missingness in the final course grade was only negatively associated with students' Time 1 self-efficacy for self-regulated learning scores (r = -.10, p < .001). These findings indicate that outcome variable data can be considered to be missing at random with respect to covariates.

To answer the first research question (i.e., “What is the relationship between students’ self-efficacy for self-regulated learning, academic procrastination, and course performance?”), a cross-lagged panel model was analyzed with high school GPA as a control variable, repeated measures of self-efficacy for self-regulated learning and academic procrastination, and the two course performance variables (i.e., self-rated performance, final course grade) as outcomes. As depicted in Figure 1, self-efficacy for self-regulated learning and academic procrastination were hypothesized to have autoregressive (direct effects on themselves over time) and cross-lagged paths (direct effects on each other over time). The goal of cross-lagged panel models is to estimate influences between different variables with consideration of their previous values (Kline, 2016). To account for the effect of students’ prior achievement, I also added regression paths from high school GPA to the mediators (i.e., self-efficacy for self-regulated learning and academic procrastination at Time 2) and the course outcomes (i.e., self-rated performance and final course grade). The MODEL INDIRECT command was added to estimate the eight indirect effects of self-efficacy for self-regulated learning and academic procrastination at Time 1 through their values at Time 2 on course performance.

The maximum likelihood estimator with robust correction (MLR) was used to account for non-normality and to provide optimal parameter estimates for missing data in endogenous variables (full information maximum likelihood; FIML). To avoid losing responses due to a missing value on one or more observed covariates, the three variables

Figure 1

Overall Analytic Design



(i.e., high school GPA, self-efficacy for self-regulated learning and academic procrastination measured at Time 1) were brought into the model by estimating their means, variances, and covariances (Muthén et al., 2017). The TYPE = COMPLEX option was also included in the Mplus script to account for the clustering of students within class sections. Model fit was evaluated with not only the chi-square test and its associated *p* value (e.g., exact fit is indicated by a nonsignificant result at the .05 threshold; Asparouhov & Muthén, 2018), but also cutoff values of other indices of fit such as root mean square error of approximation (RMSEA $\leq$ .06), comparative fit index (CFI $\geq$ .95), standardized root mean squared residual (SRMR $\leq$ .08) (Hu & Bentler, 1999).

Only one control variable (i.e., high school GPA) was included in the model described above. Although other control variables might be interesting to include (e.g., first-generation student status might be related to students' beliefs about their self-regulatory capabilities), adding them to the model could have resulted in a model identification issue (i.e., estimating more parameters than the number of clusters—35 course sections). Tests of mean differences nevertheless indicated that students did not differ in their endorsement of the main self-reported variables as a function of their parents' college education status. For example, no differences in self-efficacy for self-regulated learning were observed between first-generation and continuing-generation students at Time 1 or Time 2, $t(1206) = -0.99$, $p = .32$ and $t(895) = -1.26$, $p = .21$. Likewise, students' academic procrastination did not differ by students' first-generation status at either time point, Time 1: $t(1198) = 0.20$, $p = .84$ and Time 2: $t(894) = 0.16$, $p = .87$.

Other control variables measured at the instructor level could be related to student-reported variables. In particular, instructors who had no previous online teaching experiences might not have provided instructional support to help students self-regulate their learning. To further explore this possibility (in a rudimentary manner), I compared the self-efficacy beliefs and procrastination levels reported by students whose instructors had a least one year of experience teaching online to those whose instructors did not have this experience. Teaching experience appeared unrelated to students' mean response levels at Time 1 and 2, (for self-efficacy for self-regulated learning: Time 1, $t[19] = -0.17$, $p = .87$ and Time 2, $t[19] = -0.68$, $p = .50$; academic procrastination: Time 1, $t[19] = 0 .29$, $p = .77$ and Time 2, $t[13.4] = 0.75$, $p = .46$). Thus, this variable was not additionally considered in the main analyses.

To answer the second research question (i.e., "What did students report as the most challenging aspect(s) of their asynchronous online course?"), students' open-ended responses about the most challenging part of their asynchronous courses at both time points were imported into the MAXQDA software for qualitative data analysis. Inductive coding procedures were used to identify patterns emerging in students' responses after a team of three coders reached a consensus on a list of codes and definitions (Miles et al., 2019). All discordant codes were discussed until agreement was reached between three coders. Data displays were created to show overall patterns in coding frequencies that emerged at each time point during Fall 2020.

Students' self-efficacy for self-regulated learning and academic procrastination scores were used to select distinct groups of students at each time point to answer the third research question: What are the major challenges experienced by students with low and high levels of self-efficacy for self-regulated learning and academic procrastination? Specifically, students were classified into two groups (Low vs. High) based on their levels of self-efficacy for self-regulated learning or academic procrastination at each time point. "Low" was used to characterize any individual who scored lower than one standard deviation below the mean. "High" was used to characterize any individual who scored higher than one standard deviation above the mean. I then compared "high" and "low" students' perceptions of the most challenging aspects of their asynchronous online courses to more clearly understand their experiences and to identify possible sources of support for students struggling the most with self-regulation (e.g., Cogliano et al., 2022). Pearson's chi-square tests were conducted in MAXQDA to examine group differences by the "high" and "low" levels of self-efficacy for self-regulated learning and academic procrastination in the coding frequencies assigned to students' responses (%).

CHAPTER 4. RESULTS

This chapter presents the results of the analyses used to answer each research question. For the quantitative phase, I first present the descriptive statistics for and correlations between the numeric variables of students' beliefs, behaviors, and course performance. I then describe the results of cross-lagged panel model estimating the relationships between the variables. For the qualitative phase, I describe the results of the inductive coding of students' perceived challenges in their asynchronous online courses. Lastly, to jointly understand students' quantitative and qualitative responses, I compare differences in the perceived challenges described by students with low and high self-regulatory efficacy beliefs and low and high levels of academic procrastination, respectively.

Relationship Between Self-Regulatory Beliefs, Procrastination, and Performance

In the quantitative analyses, undergraduate students' self-efficacy for self-regulated learning and procrastination behaviors were significantly associated with each other and performance in asynchronous online learning courses. Descriptive and bivariate correlation analysis revealed that students with higher high school GPAs tended to report higher self-efficacy for self-regulated learning and lower academic procrastination at both time points (see Table 1). Each variable was not perfectly normal but had absolute skewness less than 2 and absolute kurtosis less than 7 (Curran et al., 1996). Students' self-rated course performance was positively correlated with their actual final course grades, which means that students who favorably evaluated their own course performance tended to earn higher grades. Students' self-efficacy for self-regulated learning at Time 1 was positively correlated with their self-efficacy for self-regulated learning at Time 2 but

Table 1

Summary of Means, Standard Deviations, and Correlations

Variable	*n*	*M*	*SD*	1	2	3	4	5	6
1 Self-efficacy for self-regulated learning (T1)	1,208	5.10	0.74	–					
2 Self-efficacy for self-regulated learning (T2)	897	5.03	0.87	.45***	–				
3 Academic procrastination (T1)	1,200	2.71	1.17	-.52***	-.32***	–			
4 Academic procrastination (T2)	896	2.78	1.35	-.33***	-.54***	.48***	–		
5 High school GPA	1,111	3.56	0.40	.10**	.09*	-.09**	-.10**	–	
6 Self-rated performance	902	3.09	0.82	.28***	.60***	-.21***	-.40***	.16***	–
7 Final course grade	1,191	3.47	0.86	.15***	.32***	-.14***	-.28***	.31***	.56***

Note. Missing data were handled using full information maximum likelihood.
*p < .05, **p < .01, ***p < .001.

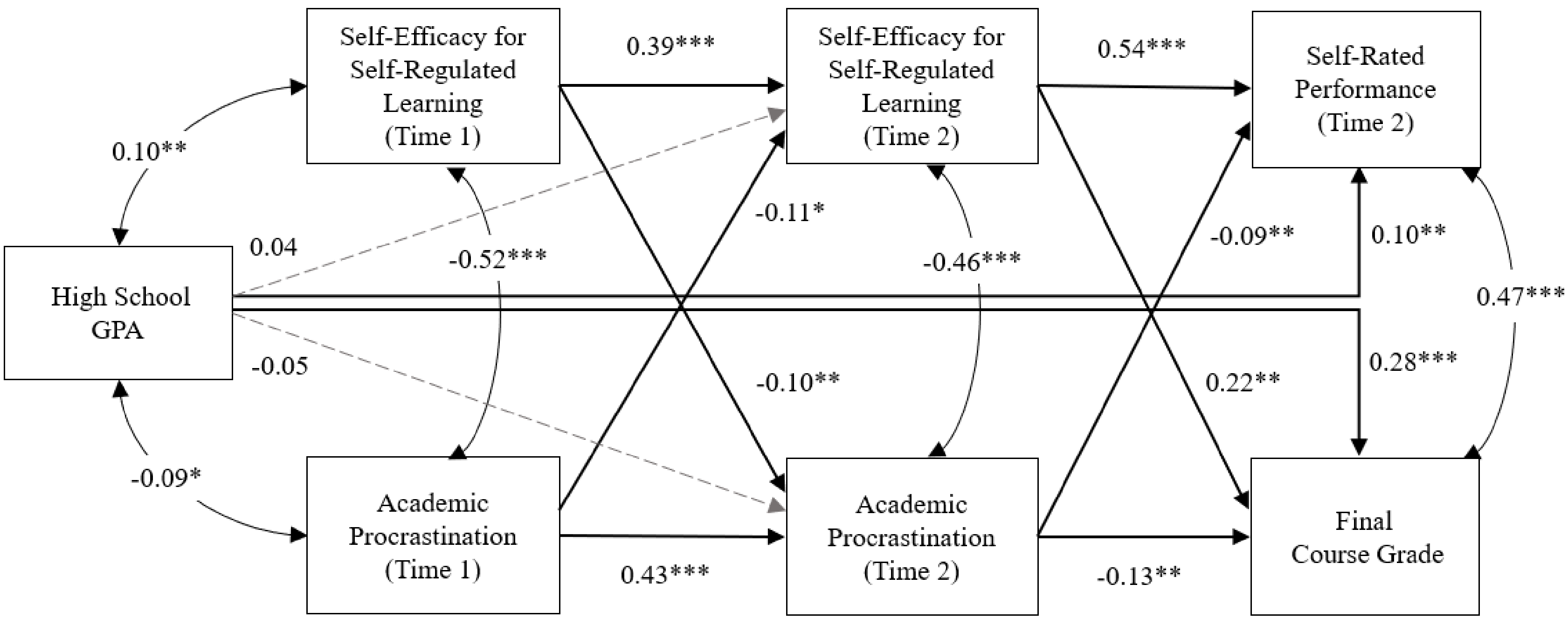
negatively correlated with their academic procrastination at Time 1 and 2. Students who reported higher academic procrastination at Time 1 tended to report higher procrastination and lower self-efficacy for self-regulated learning at Time 2.

The first main purpose of this study was to estimate interdependency between self-efficacy for self-regulation and academic procrastination as related to course performance. Figure 2 shows the standardized results of the hypothesized cross-lagged panel model to answer the first research question with taking into account students' high school GPA as a control variable. The model had a good fit to the data, $x^2(4) = 1.20$, $p = .88$, RMSEA [90% confidence interval] < .001 [.00, .02], CFI = 1.00, SRMR = 0.01.

Students who reported higher self-efficacy for self-regulated learning at Time 1 were more likely to report higher self-efficacy for self-regulated learning ($\beta = 0.39$, $p < .001$) and lower academic procrastination ($\beta = -0.10$, $p = .001$) at Time 2. Students who reported higher academic procrastination at Time 1 were more likely to report higher academic procrastination ($\beta = 0.43$, $p < .001$) and lower self-efficacy for self-regulated learning ($\beta = -0.11$, $p = .026$) at Time 2. These results took into account students' high school GPA as a control variable, even though it was not significantly associated with the two self-reported variables at Time 2. Students who reported higher self-efficacy for self-regulated learning and lower academic procrastination at Time 2 earned better course grades (respective path coefficients were $\beta = 0.22$, $p = .003$ and $\beta = -0.13$, $p = .004$) and rated their own performance more positively ($\beta = 0.54$, $p < .001$; $\beta = -0.09$, $p = .006$, respectively). Students who had a higher high school GPA tended to earn higher grades ($\beta = 0.28$, $p < .001$) and rate their course performance more favorably ($\beta = 0.10$, $p = .004$). Based on the comparison of standardized path coefficients, students' high school

Figure 2

Results of Cross-Lagged Panel Model



Note. Single-headed arrows = standardized regression paths, double-headed arrows = correlations. Dashed lines indicate nonsignificant relationships and solid lines indicate significant relationships.

*$p < .05$, **$p < .01$, ***$p < .001$

GPA had the strongest effect on their final course grades. By contrast, students' self-efficacy for self-regulated learning at the end of the semester was more strongly associated with their self-rated course performance. The study variables explained 19% of the variance in students' final course grades and 37% of the variance in their self-rated performance.

An examination of the indirect effects on the final course grades revealed that students who reported higher self-efficacy for self-regulated learning at the self-regulation variables Time 1 were more likely to report higher self-efficacy for self-regulated learning at Time 2, which resulted in higher final course grades ($\beta = 0.09$, $p = .007$). This finding suggests that individuals who sustained a strong sense of self-efficacy throughout the semester performed better. In addition, students' self-efficacy for self-regulated learning at Time 1 was positively associated with final course grades through its inverse association with procrastination at Time 2 ($\beta = 0.01$, $p = .026$). In other words, individuals with a strong sense of self-efficacy were less likely to procrastinate and thus performed better. Students who reported higher academic procrastination at the beginning of the semester tended to report higher academic procrastination and lower self-efficacy for self-regulated learning at the end of the semester, which resulted in lower final course grades ($\beta = -0.06$, $p = .004$; $\beta = -0.03$, $p = .005$, respectively).

Similar patterns were found when investigating the indirect effects of the self-regulation variables on the other outcome variable of interest—self-rated performance. Students who reported higher self-efficacy for self-regulated learning at Time 1 were more likely to report higher self-efficacy for self-regulated learning and less likely to report procrastinating at Time 2, which was positively associated with their own evaluation of their overall course performance ($\beta = 0.21$, $p < .001$; $\beta = 0.01$, $p = .037$, respectively). By contrast, students who reported higher academic procrastination at Time 1 were more likely to show greater academic procrastination and lower self-efficacy for self-regulated learning at Time 2, which resulted in less favorable self-rated course performance ($\beta = -0.04$, $p = .006$; $\beta = -0.06$, $p = .015$, respectively). Overall, findings from the quantitative phase indicate that students' personal capability beliefs and procrastination behaviors are significantly interdependent and have positive and negative impacts on their course performance, respectively.

Identification of Primary Challenges in Asynchronous Online Courses

The aim of the second research question (i.e., "What do students report as the most challenging aspect(s) of their asynchronous online courses?") was to understand students' learning experiences, and particularly their struggles, in their asynchronous online courses during COVID-19. Broad emerging patterns were identified from students' responses to the open-ended survey items (i.e., What has been the most challenging part of [Course]?) administered at the beginning and end of Fall 2020. Of the full sample, 1,067 students responded to the question at Time 1 (September) and 777 students responded to the open-ended question at Time 2 (November). Though the rank order of the most frequently assigned codes changed slightly across time points, the overall patterns indicated that students experienced similar challenges for the duration of their course (see Table 2). Thus, illustrative examples of the challenges students experienced in their asynchronous online courses are presented below regardless of when they occurred during the semester.

Table 2

Frequencies (%) of Codes Assigned to the Most Challenging Aspects of One's Asynchronous Online Courses

Codes	Definition	Sample Responses	Time 1 (n = 1,067)	Time 2 (n = 777)
Time Management	The response mentions challenges with managing one's time and habits to complete course materials on time.	- Finding a way to manage my time and get everything done on time - Assignments being overlooked and staying on top of schoolwork	22.3%	19.2%
Workload/Assignments	The response mentions challenges with workload, course assignments, and assignment submission.	- The amount of course material to learn - Homework, can be hard to find all the answers in my notes or book	13.8%	16.0%
Online Modality	The response mentions challenges with being online, not being in-person, or asynchronous aspects of learning.	- No scheduled lectures and only being required to learn from [platform] - With it being fully online, it is easy to disengage	15.6%	13.8%
Understanding/Application	The response mentions challenges with understanding/applying course content or memorization and content itself.	- Trying to understand the course material - Application of the content - Having to memorize a lot of this information	14.4%	11.8%
Performance/Evaluation	The response mentions achievement of grades or exams themselves as a challenge in the course.	- The exams have had some difficult questions on them - Keeping a good grade	10.2%	14.5%
Social Interaction	The response mentions challenges with the presence or lack of communication/collaboration with peers and instructors.	- A challenging aspect is not being able to be in person to work with peers - I cannot interact directly with the professor during class since it is online	4.2%	6.8%

Table 2 *(continued)*

Codes	Definition	Example	Time 1 (n = 1,067)	Time 2 (n = 777)
Motivation	The response mentions challenges with being motivated for or having an interest in their coursework.	- Trying to motivate myself to do the work - Nothing to get me motivated or excited to learn	4.4%	4.4%
Concentration/Notetaking	The response mentions challenges with paying attention or taking notes.	- Being able to focus on the course work - Taking notes and being attentive for the entirety of the lectures	3.0%	2.3%
Teacher/Teaching Quality	The response mentions low teaching quality, a lack of organization and grading guides, and/or some aspects of the personality of their instructor as a barrier in the course.	- The professor is disorganized Rubrics are posted after assignments are due - The professor's inability to teach effectively	2.0%	6.6%
Student Well-Being/ Workspace	The response mentions dealing with emotional/health problem or an issue of having proper places to study with necessary resources.	- I don't have the money to buy the book so I can't finish the homework completely - Difficulty finding a distraction free area to study - Wi-Fi in my dorm	2.1%	0.9%
Other	The response does not fall into existing categories or is too general.	- Everything - Getting adjusted - COVID	4.2%	5.1%
No Challenge	The response includes "N/A" or "nothing".	- It hasn't really been challenging - N/a, this class is by far my favorite	14.2%	8.2%

Note. Because about 9% of responses at Time 1 and 2 received multiple codes, column percentages do not total to 100%.

The most frequent code assigned to the challenges students described was Time Management (22.3% of all responses at Time 1, 19.2% at Time 2). Students expressed difficulty managing the timing or speed of their course engagement in the asynchronous online learning environment. In particular, students felt challenged by their assignment schedules (e.g., “Trying to stay organized with assignments and their due dates”) and in making sure assignments were turned in on time (e.g., “Holding myself accountable to complete the work each week in a timely manner”). Some students attributed their challenges with time management to the unfamiliar course delivery modality (e.g., “Just making sure I stay on schedule. But that is a personal issue I have been dealing with trying to adjust to online classes”). Other students explicitly described challenges in watching instructors’ recorded videos within the timeline suggested on the course syllabus and in their personal schedules. One student directly pointed out their personal habit of procrastination (e.g., “Being asynchronous has been great but there were times where I would have a bad habit of waiting until the last minute to start on assignments”).

The code Workload/Assignments was assigned when students noted the burden of course requirements or content as the most challenging part of their course (13.8% at Time 1, 16.0% at Time 2). Students often perceived challenges in the overall amount of work required (e.g., “The increased workload of the course”) and in specific types of assignments such as reading, writing, or discussion (e.g., “The very long reading assignments”). Students who described their excessive workload often reported feeling distressed. For example, one student wrote, “There have been multiple times where the course load has been too much and I felt pretty overwhelmed.” Students sometimes attributed their difficulty with assignments to unclear course structures or a lack of information (e.g., “There's no rubric, so sometimes I feel like I'm taking a shot in the dark”). Some students also described difficulty understanding how to submit their assignments (e.g., “Just trying to figure out how to use the different platforms used in this class to submit work”). Although students’ responses about their assignments and workload sometimes also implied difficulty with time management, in these instances, they did not mention time explicitly.

Many students perceived the instructional modality itself (coded as Online Modality) as the most challenging aspect of their asynchronous online courses (15.6% at Time 1, 13.8% at Time 2). Responses revealed that students were more familiar with in-person classroom settings that were more common before COVID-19. Some students indicated that being fully online was not easy for them (e.g., “Just being more of an in person learner has been challenging to adjust to the virtual”). Other students felt as though the web-based learning classroom was not an authentic learning space. For example, one student explained that “not having an actual class” was the most challenging aspect of their asynchronous online course. Another student felt challenged in “learning not in a real time situation.” Although recorded videos or learning management systems had already been used in certain schools and learning settings, students reported that the technology was a barrier for their learning. For instance, students pointed out “learning all new material at a fast pace over a screen” or “learning completely online through videos” as the most challenging aspect in their courses. In addition, some students noted the lack of synchronous class meetings as a challenge. (e.g., “No Zooms”). Although asynchronous online courses should be assumed to lack synchronous meetings, and instead use emails or discussion boards for written communication, some students seemed to identify live conversation as key to authentic learning spaces.

The fourth theme to emerge from students' responses about challenges was related to understanding and application of their course content (14.4% of responses at Time 1, 11.8% at Time 2). For example, one student reported, "I think the content is very challenging." Another wrote, "It's just harder material, not anyone's fault." Some students reported that it was difficult to understand what they were learning because of insufficient instructional materials for their needs (e.g., "As student with a visual disability and ADHD, it is hard to follow along on the lectures, and understand when there is no PowerPoint to follow along with"). Some students indicated self-regulatory challenges by noting the additional efforts that were required to learn (e.g., "Occasionally having to rewatch lectures to ensure I understand a topic"). Another noted that their online course required "a lot of memorization, so I have to be on top of what I am learning and keep up with it."

The code Evaluation/Performance was assigned to responses that conveyed challenges with course assessments (10.2% at Time 1, 14.5% at Time 2). Students often reported that their quizzes or exams were challenging to them (e.g., "The most challenging aspect of this course was the exams, I felt I could have done better on them than I did"). Some felt that achieving desirable learning outcomes was not easy, but they also questioned the value of the assessments used in their classes (e.g., "The test for sure [is the most challenging aspect]. I feel that I have mastered the content, but this does not reflect on my test").

Students also experienced challenges in Social Interaction (4.2% at Time 1, 6.8% at Time 2). This code was used when students' responses conveyed barriers to or a lack of communication and collaboration with peers and instructors. Whereas some students struggled in their learning context without immediate interactions with instructors (e.g., "Distance from professor") or peers (e.g., "Feeling connected to my classmates virtually"), others experienced challenges related to the social interactions required in their asynchronous online course (e.g., "The group work is absolutely horrible. At least, in assigned groups").

A small number of students indicated that the most challenging aspect of their asynchronous online courses was staying motivated to engage in their course or developing or maintaining an interest in their coursework (Motivation; 4.4% at both time points). Some noted a lack of academic motivation to work on their course materials (e.g., "Nothing to get me motivated or excited to learn"). Some also expressed low interest in the topics they were learning: "I wish I was more into the topic."

Students described difficulty in concentrating (e.g., "Paying attention to non-mandatory recorded lectures") and notetaking in their course (e.g., "The most challenging part has been knowing what notes to take during the video lectures"). Such responses were assigned the code Concentration/Notetaking (3.0% at Time 1, 2.3% at Time 2). A few students noted that their instructors' low teaching quality or a lack of structures was the most challenging aspect of their courses, which was more emerged at the end of the semester. Even fewer students mentioned their personal health issues or a lack of necessary resources (e.g., internet connection) as barriers to their learning.

Unlike other codes that signified at least one challenge, the "No Challenge" code was assigned to responses indicating that the student did not experience any challenges in their asynchronous online courses (14.2% at Time 1, 8.2% at Time 2). For example, students directly emphasized their lack of perceived challenges (e.g., "I do not believe there is anything challenging about it") or gradual adjustment to their courses (e.g., "Nothing really, I understand the class dynamics much better now"). Some students also mentioned the characteristics of their course materials but did not perceive them as challenging (e.g., "Some of the reading was long, but overall I did not find this course challenging rather it was interesting"). One student even mentioned that "The assignments are great to help me with my learning and understanding for this class." Some also attributed their lack of challenges to the high quality of teaching their instructor provided. One student wrote, "So far I have enjoyed the class and have not felt that there have been any challenges related to how the course is structured or instructions."

Comparison of Challenges Based on Self-Regulatory Beliefs and Procrastination

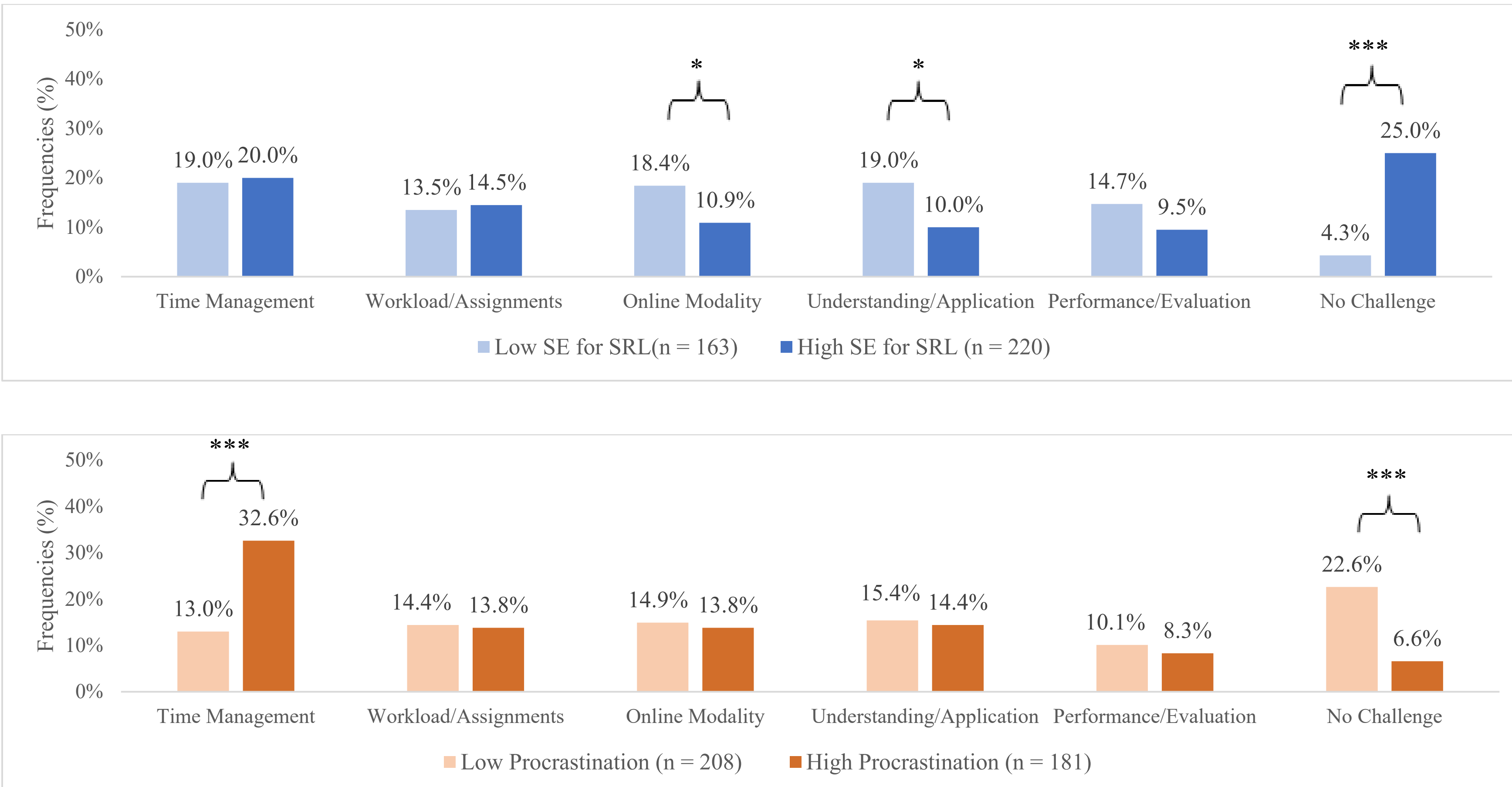
In the last phase of synthesizing quantitative and qualitative data, I was attentive to whether students with different self-regulatory beliefs and behaviors might perceive different challenges in their asynchronous online courses. To answer the third research question (i.e., "What are the major challenges experienced by students with low and high levels of self-efficacy for self-regulated learning and academic procrastination?"), I first identified students who reported exceptionally low and high self-efficacy for self-regulation and low and high levels of academic procrastination. I then compared the major challenges they described. Figures 3 and 4 compare the frequencies of codes assigned to the responses written by students with low and high self-efficacy for self-regulated learning, and low and high self-reported academic procrastination. I focused on the six most frequent codes, all of which were assigned to more than 5% of respondents at both time points.

At the beginning of their asynchronous online courses in Fall 2020, students who had low self-efficacy for self-regulation were significantly more likely to describe their primary challenges as relating to the course delivery format, $\chi^2(1) = 4.34$, $p = .04$, and understanding of course materials, $\chi^2(1) = 6.39$, $p = .01$, compared to students with high self-efficacy for self-regulation. One student with low self-efficacy for self-regulation noted that “The most challenging part is that it is fully online. All of my other classes are either hybrid or meet virtually on zoom during the original scheduled class time.” As for understanding course materials, another student with low self-efficacy for self-regulation explained that “teaching myself” was the most challenging aspect of their asynchronous online course. However, regardless of their self-efficacy level, students were equally likely to perceive challenges related to time management, course workload, and course assessments.

In contrast, students who rated themselves as high procrastinators were significantly more likely to describe time management skills as the most challenging aspect of their courses than were those who rated themselves as low academic procrastinators, $\chi^2(1) = 21.63$, $p < .001$. Students who had a high tendency to procrastinate in their work described the challenge of “Keeping up with it being all online and at your own pace” or of the way their course was structured (e.g., “Figuring out when Discussion Posts are due. They weren't included on the course schedule on the syllabus,

Figure 3

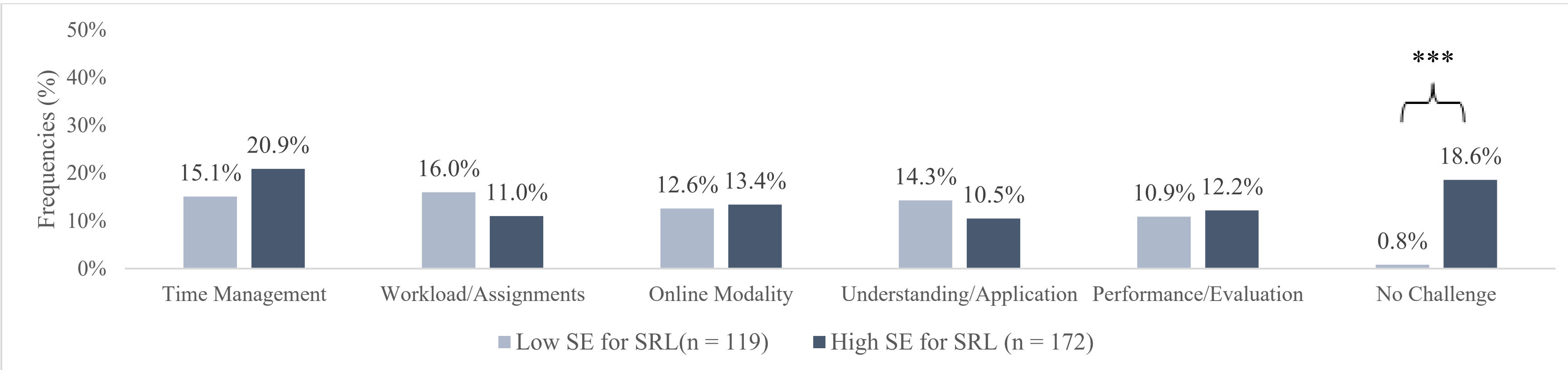
Challenges by Levels of Self-Efficacy for Self-Regulated Learning and Academic Procrastination (Time 1)

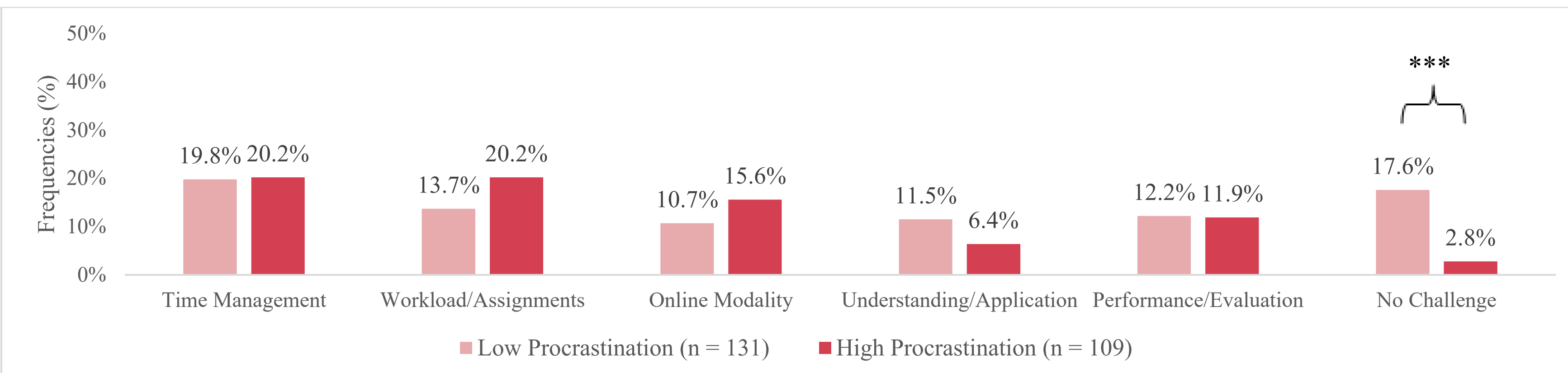


**p* < .05, ***p* < .01, ****p* < .001.

Figure 4

Challenges by Levels of Self-Efficacy for Self-Regulated Learning and Academic Procrastination (Time 2)





*$p < .05$, **$p < .01$, ***$p < .001$.

so I missed the first few"). No differences in the frequency of other perceived challenges emerged between students with high and low levels of procrastination.

The proportion of responses reflecting no challenge differed significantly between students with low and high self-efficacy for self-regulation, $\chi^2(1) = 29.59$, $p < .001$. Students with high self-efficacy were more likely to report no challenges in their courses. In particular, one high self-efficacy student wrote, "I have not found anything overly challenging as long as you put in your due diligence your grade will reflect that in this class."

Similarly, responses from students with low procrastination scores were more likely to reflect no challenge than were those from students with high procrastination, $\chi^2(1) = 19.17$, $p < .001$. This response from one student who reported rarely procrastinating illustrated the supporting role played by a strong self-regulatory skillset (e.g., "Nothing so far [is challenging], I've been keeping up with my assignments and getting them done right away").

Similar patterns were found in the challenges reported by each group near the end of the semester (Time 2) with one exception. Students who had high self-efficacy for self-regulation were more likely to state that they did not experience challenges in their courses, $\chi^2(1) = 22.08$, $p < .001$. Similarly, students who were classified as low procrastinators tended to say that they did not have challenges in their courses, $\chi^2(1) = 13.50$, $p < .001$. Some students simply mentioned that they did not experience challenges, whereas others noted the reasons for which they did not perceive any challenges in their courses. For instance, one highly confident student highlighted her ability to adapt to the demands of her course: "Some of the exam material at the beginning was a little tough but I managed to work through it." Another student who had low procrastination explained that the value of the course made it seem less challenging (e.g., "I haven't found anything too difficult because I enjoy it so much").

Among learners with high self-efficacy for self-regulated learning and low procrastination, many still described experiencing challenges in their classes. In fact, some challenges were equally likely to be reflected in the responses of learners with low and high self-efficacy for self-regulation and low and high procrastination. For instance, students who had low self-efficacy for self-regulated learning were just as likely as those with high self-regulatory beliefs to mention their course modality as their main challenge, $\chi^2(1) = 0.04$, $p = .85$. Time management was almost equally mentioned by high and low procrastinators as the most challenging aspect of their asynchronous online courses at the end of the semester, $\chi^2(1) = 0.004$, $p = .95$. A low procrastinator even described that "asynchronous classes can be challenging. I have to work ahead and make sure I have enough time to complete all my assignments."

Overall, students perceived salient challenges in time management, course modality and materials, and cognitive and behavioral engagement in their fully asynchronous online courses during Fall 2020. In particular, students with high self-efficacy for self-regulated learning and low academic procrastination tended to perceive fewer challenges in their learning experiences at both time points during the semester. In terms of experienced challenges, differences in the responses of students by their levels of self-regulatory beliefs and procrastination behaviors were more prevalent at baseline than at the end of the semester.

CHAPTER 5. DISCUSSION

With the expansion of web-based courses in all learning settings, self-regulated learning has been emphasized as one of the key factors explaining individual differences in learning and performance (Hodges, 2005). When the COVID-19 pandemic hit the United States, asynchronous online courses allowed students greater flexibility in how they could engage in their course without in person meetings and provided safety at a time of immense public health concerns. However, the rapid shift to an asynchronous online instructional environment may have placed added burden on students' self-regulatory skills during Fall 2020 (Calma-Birling & Zelazo, 2022). Previous research showed that not all students successfully adjusted to the drastic changes in their learning environments in Spring 2020 (e.g., Usher et al., 2021).

This study aimed to obtain a more comprehensive understanding of college students' self-efficacy for self-regulated learning and procrastination behaviors as predictors for success in asynchronous online learning courses during Fall 2020. Self-efficacy for self-regulated learning has received researchers' attention as a predictor of academic procrastination in traditional learning settings like face-to-face courses (Klassen et al., 2008). However, the two constructs have not been examined reciprocally or in asynchronous online courses. In the quantitative phase, this study investigated the bidirectional relationship between students' self-efficacy for self-regulated learning and academic procrastination as well as its impacts on course performance. Although online learning during COVID-19 might have been difficult for college students, less is known empirically about what students perceived as the most challenging aspects of learning in their fully asynchronous online courses. In the qualitative investigation, I examined the main challenges students described in their open-ended responses. In addition, I examined whether students' perceived challenges in their asynchronous online courses might differ by their levels of self-regulatory beliefs and procrastination behaviors.

Self-Regulatory Beliefs and Procrastination: Reciprocity and Effects

The quantitative results of the cross-lagged panel model indicated that students who believe in their capabilities to manage and regulate their own learning were less likely to put off doing their course assignments. Furthermore, students who reported higher tendencies to procrastinate at the beginning of the semester tended to have lower self-efficacy for self-regulation. These results support the theorized argument that students' beliefs about their capabilities and their corresponding behaviors are reciprocally related (Bandura, 1997; Zimmerman & Campillo, 2003). Researchers have previously reported a negative relationship between self-efficacy for self-regulation and academic procrastination, but they have typically focused on a unidirectional relationship (i.e., self-regulatory beliefs predicting procrastination). More attention is needed to examine whether mismanagement of time can influence as well as be influenced by one's self-regulatory beliefs (Wolters & Brady, 2021).

Researchers have emphasized the need to support students' perceptions about their self-regulatory capabilities because self-doubt can undermine the use of effective learning strategies and self-regulatory skills (Usher & Pajares, 2008). However, findings from this study indicate that educators should simultaneously target students' personal capability beliefs and procrastination behaviors, particularly in fully online asynchronous learning. In clinical settings, cognitive behavioral therapies have helped those who struggle with procrastination by changing both inaccurate perceptions about their personal capability and ineffective academic habits for time management (e.g., Rozental & Carlbring, 2013). In a fully web-based, asynchronous learning context, instructors can insert observational learning opportunities using recorded videos or written materials that can help students improve their self-efficacy for self-regulated learning and learn more adaptive time management skills from virtual or live peer role models (e.g., Cogliano et al., 2022).

Another finding of the quantitative investigation suggests that supporting students' self-regulatory beliefs and decreasing their procrastination behaviors can contribute to student success in asynchronous online learning environments. This study found that students who reported higher self-efficacy for self-regulated learning and lower academic procrastination at the beginning of the semester were more likely to earn better final grades (one marker of learning) and to rate their own performance more favorably, even after controlling for prior achievement. Although college students are often expected to be more self-regulated or responsible for their academic work, they are not equally prepared to manage their self-paced asynchronous online courses. Thus, adding required deadlines and structured directions to learning materials (e.g., recorded lectures) is important for helping more students remain engaged in their asynchronous online courses (Hogan & Sathy, 2022). Given that asynchronous online modalities are becoming more common in higher education and even in the workplace, promoting students' self-regulatory beliefs and behaviors that support their academic performance is critical both during and after COVID-19.

Managing Self-Regulatory Challenges in Asynchronous Online Learning

Inductive qualitative coding of college students' responses was used to identify what students perceived as the most challenging part of their asynchronous online courses at the beginning and end of Fall 2020. Students confronted various challenges during COVID-19, yet there is an empirical need to understand, from their perspectives, what types of challenges emerged in order to better support their learning. Overall, the findings in this study indicate that self-regulation was a salient challenge for students taking asynchronous online courses. In particular, at both time points, the most frequently reported challenge was time management. Although studies examining college students' perceived challenges during COVID-19 have shown that students reported difficulties completing requirements in their online courses, they often asked participants about their online learning experiences broadly (e.g., Hensley et al., 2022). This study contributes to the literature by describing the types of challenges experienced by students in one specific learning context—asynchronous courses. The findings suggest that educators can improve students' performance by supporting time management. For example, instructors could use regular assignment reminders and provide proactive learning opportunities for time management skills at the start of the course. Or, they might consider allowing students to set multiple deadlines for certain assignment and submit subtasks gradually over time.

Another salient self-regulatory challenge that students reported experiencing was feeling burdened with the number of assignments in their online courses. When students perceive an excessive workload, they are often less motivated to work on their given tasks. Instructors can help make the workload seem more manageable by dividing course materials into multiple segments with gradually increasing difficulty and by removing redundant tasks (Eitel et al., 2020). At the same time, students may also need to reflect on why they perceive their assignments as challenging or feel overwhelmed about completing them. For instance, some students may feel more overwhelmed because of their inexperience in asynchronous online courses. Structures that allow open communication between instructors and students about course assignments and deadlines early in the semester can be helpful to alleviate students' perceptions of excessive workload (Thompson, 2007).

Most, if not all, asynchronous online courses are delivered via a learning management system (LMS), an online platform for content delivery. Although asynchronous online platforms have been used in various learning settings in higher education, this study found that many students still described the instructional modality as the primary challenge in their fully asynchronous online courses. Instructors can make use of LMS tools to provide short orientation videos and online materials about how to navigate course contents each week (or by topic). Inserting social cues within the LMS by showing how many students are working on the corresponding web pages or modules can be helpful for students' co-regulation of course requirements with their classmates and can increase feelings of connectedness in the online course. This is aligned with the notion of modality-specific interventions such as using common video meeting signals to foster students' engagement in the context of synchronous online courses (e.g., Hills et al., 2021). Given that instructors may not always be familiar with the most updated tools available within certain LMS, they can benefit from professional development opportunities about asynchronous online courses. For instance, institutional supports that provide opportunities for instructors to share the pedagogical and technological practices they use in asynchronous online courses with other instructors and learners can help improve online instruction (Paskevicius & Irvine, 2019). Comparative studies or randomized experiments can be helpful for further investigating differences in learners' perceived challenges in other modalities.

Examining Extreme Cases: Individual Differences in Perceived Challenges

Examining the patterns of challenges between the subgroups of students with distinct self-regulatory beliefs and behaviors highlights various learning experiences in asynchronous online courses during Fall 2020. At the beginning of the semester, students who doubted their self-regulatory capabilities were more likely to perceive challenges related to the instructional modality, course content, and required skills than were those with strong personal efficacy beliefs. By contrast, students who reported high academic procrastination were more likely to report a lack of time management skills as the most challenging aspect of learning in their courses than were those with low academic procrastination. These findings indicate that students' self-regulatory beliefs and behaviors, though related, are not the same variable based on the different patterns in perceived challenges. Future interventions designed to improve self-regulated learning should be expanded to support both low personal capability beliefs and self-defeating behaviors rather than focusing on only one of them.

Consistently across the semester, students who were highly self-efficacious about their own self-regulation skills for learning or who reported lower levels of academic procrastination were more likely to describe that they did not have any challenges in their asynchronous online courses. As Zimmerman (1986) noted, self-regulated learners "select, structure, and create environments that optimize learning" (p. 308). Taking students' closed- and open-ended responses together indicates that self-regulated learners can demonstrate potential for adapting to the challenges of their courses. Specifically, the findings support that high self-efficacy for self-regulation and low academic procrastination, as important aspects of the dynamic self-regulatory processes, can positively contribute to the likelihood that students complete their asynchronous online courses successfully with fewer challenges.

In terms of what kinds of challenges students experienced, some with high self-efficacy for self-regulation described challenges similar to those described by students in the low self-efficacy group. As did their high procrastinating peers, students with low procrastination behaviors also described challenges completing their assignments on time and managing their schedules in their asynchronous online courses at the end of the semester. The similar patterns of challenges reported could indicate a distinction between perceiving that tasks are under one's personal control and perceiving those tasks as challenging or difficult (Trafimow et al., 2002). Even though many students described common challenges at the end of the semester, they managed their asynchronous online courses differently with distinct self-regulatory beliefs and behaviors. These findings point to the importance of understanding students' heterogeneity in self-regulated learning.

Limitations and Future Directions

Overall, this study indicates the need of supporting both undergraduate students' self-efficacy for self-regulated learning and avoidance of academic procrastination behaviors in asynchronous online courses. However, several limitations of this study should be acknowledged.

First, the findings of this study may not be generalizable to different time points even during the COVID-19 pandemic. Compared to their experiences from the sudden change of instructional modalities in the middle of spring semester in 2020, students could have some time to prepare for their upcoming fall semester and fully asynchronous online courses. However, as this study found, students might not have had enough opportunities to learn how to effectively manage their asynchronous online courses. Future studies need to examine how students reflect on their self-regulation in asynchronous online courses at the other points in time and after the pandemic's end. Even in similar times of crisis, the results of this study might vary if it featured different conditions. For instance, this study's sample size might have influenced the statistical significance of regression coefficients. Students' differences in their perceived challenges were not tested for the intersection of self-regulatory beliefs and procrastination behaviors due to the limited sample size.

As another limitation, the current study did not investigate why some students began their asynchronous online courses with higher self-efficacy for self-regulated learning than others. Bandura's (1997) social cognitive theory posits that students' beliefs in their capabilities can be influenced by four sources: mastery experience, vicarious experience, verbal persuasion, and physiological/affective states. Although mastery experiences have typically shown the strongest effect on self-efficacy in subjects such as mathematics, this source of self-efficacy may not be as easily assessed in the context of self-regulated learning (Usher & Weidner, 2018). Other sources of information, such as vicarious experiences, may be less frequently available in certain contexts. For instance, in asynchronous instructional contexts during Fall 2020, students might not have had sufficient opportunities to observe how classmates were managing their work effectively in their courses given that in-person or synchronous online meetings would be rarely used. This might be because many instructors were new to teaching asynchronously and had difficulty creating opportunities for students to connect with each other in the unique environment. Given that this study did not examine the impacts of instructor- or course-level efforts for cultivating social connection on students' academic motivation and achievement in asynchronous online courses, future studies can expand the findings by capturing contextual inputs in multilevel modeling.

Third, this study has limitations in focusing on students' self-reported procrastination. For the quantitative investigation, students' procrastination behaviors were measured using survey items at the beginning and end of the semester. Procrastination can be assessed in a variety of ways to identify its levels and patterns (Kim & Seo, 2015). For instance, longitudinal investigations more than one academic semester would be useful to understand college students' academic procrastination across time in college. Examining periods of course engagement by tracking when students initiated and submitted their assignments or completed watching lectures in the learning management system could also be helpful to accurately verify the individual differences among low and high procrastinators beyond their self-reports.

Fourth, students who did not respond to the open-ended question were excluded from the qualitative analysis. Comparatively less research has discussed how to handle missing data in qualitative research than in quantitative research (Singh & Richards, 2003). There can be various reasons why some participants do not choose to write, speak, or type their answers to given qualitative inquiries. Some students might not have answered the question because they experienced challenges but did not want to share them. Given that a fair number of students explicitly noted that they did not have any challenges in their courses, it is possible that others who did not experience challenges simply chose not to respond. However, the current study chose to analyze students' observed responses rather than putting unknown assumptions.

Conclusion

In their updated overview of social cognitive theory, Schunk and DiBenedetto (2020) urged researchers to pay closer attention to how students' motivation and learning behaviors operate in technology-mediated learning environments as opposed to face-to-face learning settings that have been more commonly studied. Online instructional modalities have become prominent in higher education, and asynchronous learning will likely become more commonplace. Although the change of instructional modality might have been already anticipated by educators and students, especially those whose work centers on what it means to live and learn in an information or digital age, the rapid onset of the COVID-19 pandemic did not allow the masses to adjust with necessary supports. As Bandura (1997) has remarked, "wrenching social changes are not new over the course of history, but what is new is their magnitude and accelerated pace" (p. vii). Given that instructional modalities may be more diversified and flexible in the near future with technological developments (Miao et al., 2020), students need to practice how to manage their own learning persistently and effectively in fully web-based courses. This study's findings call for more individualized attention and modality-based supports to bolster college students' beliefs in their self-regulatory capabilities and help them take proactive actions for time management, which can be ultimately linked to desirable learning outcomes in asynchronous online courses.

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VITA

JAEYUN HAN

November 30, 2022

EDUCATION

Master of Arts, Education February 2018
Ewha Womans University, South Korea
Area of specialization: Educational Psychology
Advisor: Dr. Tae Seob Shin
Thesis title: The Effect of Sources of Self-Efficacy, Mindsets Toward Self and Others on Mathematics Self-Efficacy: Moderating Effect of Social Comparison Motives

Bachelor of Arts, Education February 2016
Ewha Womans University, South Korea

MANUSCRIPTS PUBLISHED

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