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Increasing Undergraduate Student Engagement in Academics: An Ecological Momentary Intervention

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UNIVERSITY OF NORTHERN COLORADO

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The Graduate School

INCREASING UNDERGRADUATE STUDENT ENGAGEMENT IN ACADEMICS: AN ECOLOGICAL MOMENTARY INTERVENTION

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ABSTRACT

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As students enter the university environment, they are presented with various commitments that may or may not impede academic performance. With the issues of student attrition and retention, there is a need to provide further tools for students to use to monitor their performance. As students' progress to higher level coursework, expectations and time commitments increase, and self-regulation of learning becomes even more important. Researchers may be able to deliver information to help students with self-regulation of learning by leveraging new affordances in technology in students' daily lives. The purpose of this dissertation was to examine the feasibility and associated findings of an ecological momentary intervention surrounding self-regulation, motivation and study strategy utilization. This quasi-experimental study had 49 participants. The overarching project for this dissertation was a two-week intensive longitudinal design with a baseline appointment. For the in the moment assessment via a smartphone application, there were two conditions: an intervention and an assessment-only group.

This dissertation includes two manuscripts. The first manuscript examines methodological issues related to the feasibility of using multiple types of prompting (user-initiated and researcher-generated) when utilizing in the moment data collection in an educational context, specifically factors that may influence participants' response rates and compliance to the researcher protocol. The second manuscript examines motivational

and emotional differences of the same participants within a self-regulation intervention delivered in the moment via ecological momentary intervention. Specifically, I investigated motivational and emotional factors related to student behavior (as measured by reports of studying) during the monitoring time period.

In the feasibility paper, I found overall that participants responded to approximately two prompts a day and that baseline factors such as lower self-control were associated with greater missing data. I also found discrepancies between responses to in-the-same-moment study related questions (i.e., participants saying they had not studied while also reporting a subsequent amount of time spent studying), which informed which outcomes to use in the content-based manuscript. In the content manuscript, I found no condition differences between the intervention and assessment-only groups in regard to the number of user-initiated study sessions, indicating a lack of compliance to the intervention protocol. I found that academic motivation and anxiety over time were associated with the probability of reporting studying. Finally, I found moderate relationships for end of day reports of study times with the in the moment reports, suggesting a potential rounding bias.

Based upon the results, it appears there were issues with fidelity of implementation within the protocol. This could be due to the burden placed upon participants for in the moment data collection, or additional circumstances not measured within the study. In regard to lower response rates, participant compensation could have played a role due to the data collection burden. With the majority of data collection taking place during the latter part of the semester, the time of the study may have contributed to lower instances of studying as participants for various reasons (e.g., fewer assessments, already established study practices).There needs to be further refinement to the intervention protocol to be able to measure studying in the moment including direct reminders to participants about their study behaviors and ways to further develop the training protocol for initiating prompts. Additionally, waves of data collection across the course of the semester will be explored in future work.

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CHAPTER I

INTRODUCTION

Background for the Study

Retention and persistence to graduation continues to be an issue for higher education. In the university environment, a variety of situations compete for students' attention (e.g., social goals, academic clubs). According to the National Center of Education Statistics (Snyder, de Brey, & Dillow, 2016), retention rates for first year students at public universities depend on acceptance rates with 62% for open enrollment universities to 96% for universities that accept less than 25% of applicants. The six-year graduation rates for public universities range from 32% (for open enrollment) to 88% (for less than 25% acceptance). Given the wide range for retention, as well as graduation rates, further research is needed to address factors to influence student retention, particularly at universities with higher acceptance rates.

There are several programs in place at universities to help facilitate student retention including first-year experiences, seminars, and learning communities (Bean & Eaton, 2001; Tinto, 1999). In these programs, students may attend classes where they learn skills to help with the transition to university or strategies for college success. These may be independent of content-driven courses or integrated directly into courses for particular majors (Jamelske, 2009; Pascarella & Terenzini, 2005; Schnell & Doetkott, 2003). There are mixed findings regarding student successes in these programs (Hendel, 2007; Jamelske, 2009; Keup & Barefoot, 2005; Schnell & Doetkott, 2003) These programs may be useful for acclimating to the university, but they may not be as efficacious for student performance as has been speculated.

Although the majority of retention issues happen during the first year, there is evidence to show further attrition as students' progress to graduation. With the studies mentioned previously, student retention was rarely explored beyond the second year. As students' progress to harder course work, setting specific goals, time-management and self-regulation of learning become even more important (Morisano, Hirsh, Peterson, Pihl, & Shore, 2010; Zimmerman, 2008). Robbins et al. (2004) meta-analyzed 109 samples finding academic factors associated with student performance (GPA) and student retention. Specifically, they found academic goals, self-efficacy, and strategic skills were related, on average, with moderate relationships to retention. With this in mind, educators should implement practices to aid with strategy implementation and goal monitoring via self-regulated learning.

One issue with the study of student retention is the number of time points in which data are collected. By measuring performance and retention at one time a semester or year, researchers are missing the nuanced changes students go through during the semester. By studying factors that change during the semester (e.g., effort, strategy utilization, and emotional commitment), researchers have opportunities to help implement changes that contribute to increased retention. Ecological momentary assessment (EMA; Shiffman, Stone, & Hufford, 2008) is a methodology in which multiple responses are gathered within a short period of time. Researchers can gather data closer into the moment in which it happens, reducing the probability of recall bias. The two main types of prompting schedules tend to be event-based (user generated) and signal contingent (researcher generated). Using only one type of prompting has disadvantages for studying students' academic behaviors. With user-initiated sessions, researchers may miss prompts from participants if they forget to initiate a session. With signal-contingent sessions, researchers may gather some insight as to when a behavior occurred (e.g., studying), but the report may be biased depending on how long it has been since the behavior happened. One way to potentially address these issues is to incorporate multiple prompting types into a research protocol.

There have been advances using technology to help with student motivation and retention. One such program is mSuccess that has been delivered via LifeData, a smartphone app. Here students are presented with strategies designed to help promote a growth mindset (Aronson, Fried, & Good, 2002; Dweck & Leggett, 1988) and a sense of social belonging. This intervention goes back to aspects of Tinto's (1999) discussion of what makes a successful first year transition for students. Participants view stories of students who arrived at a university and how they initially felt disconnect and came to fit in with their university. These vignettes used in the mSuccess intervention give examples about how some students felt regarding their campus climate and support networks when starting university. Participants also receive information regarding fostering a growth mindset. While the mSuccess intervention shows vignettes of students moving through the transition to university, they do not provide the specific skills to help transition to university, beyond the adoption of a growth mindset. This is where further intervention research is needed regarding effectiveness of other cognitive and metacognitive strategies delivered in the moment.

Purpose and Research Questions

The purpose of this dissertation was two-fold. The first was to examine the feasibility of using multiple types of prompting (researcher-generated and user-generated) to investigate academic self-regulatory processes, emotions, perceptions of competence, and utilization of study strategies in the moment. The second was to examine whether implementing a self-regulatory intervention regarding specific goal setting and presenting examples of study strategies is associated with more consistent study time, as well as more stable academic motivation and motives.

To provide clarity for the research questions in this document, questions one through three were used for the methodological journal manuscript in chapter four. Questions four through seven were used for research questions for the content driven journal manuscript in chapter five. I present the research questions below:

Methodological Journal Manuscript Questions in Chapter IV

Q1 What factors relate to response rates (e.g., time in study, weekday vs. weekend, proximity to class time, and reminders delivered.)?

Q2 Are participants compliant in reporting of study sessions for user-initiated prompts?

Q3 Are there discrepancies among reporting of studying since last prompt (yes/no) and how much time spent studying since last prompt (hh:mm)?

Content Driven Journal Manuscript Questions in Chapter V

Q4 Are there differences in reported daily study time between conditions?

Q4a For the intervention condition, are there differences in planned versus reported end of day study times?

Q5 Are there patterns in the relationship among academic motivation and positive and negative emotions when examined over time?

Q6 Does academic motivation and emotions relate to reports of study engagement?

Q7 Are there differences in the number of initiated study sessions between intervention and assessment only conditions? What about number of completed follow-up sessions?

CHAPTER II

REVIEW OF THE LITERATURE

In this review, I focus on the theoretical orientations pertaining to the study including motivational and cognitive variables involved in self-regulation. Although there are numerous conceptualizations regarding self-regulation (Sansone, & Thoman, 2005; Winne, 1995; Zeidner, Boekaerts, & Pintrich, 2000; Zimmerman, 1986), I frame the discussion in terms of Zimmerman's (2000) social cognitive model of self-regulation. I then discuss interventions designed to aid with academic self-regulation and their associated benefits and limitations. Finally, I address the use of in the moment data collection methods and their benefits for educational research.

Self-Regulation

Self-regulation is one framework in which to investigate student engagement (Pintrich, 2000; Winne, 2001; Zimmerman, 2000). According to Zimmerman (1986), self-regulation consists of how someone is cognitively, behaviorally, and motivationally engaged in learning. Zimmerman (2008) further refined the conceptual framework to include how students use their mental abilities to influence performance. Performance then in turn influences cognitions and motivation, thus creating a feedback loop (Hattie & Timperley, 2007). In this model, there is a cyclical nature among motivation, cognitive abilities, and strategies. Self-regulation has been related positively to academic outcomes such as study success, course performance, and overall academic performance (Chen, 2002; Hadwin, Winne, Stockley, Nesbit, & Woszczyna, 2001; Heikkilä & Lonka, 2006;

Kitsantas, Winsler, & Huie, 2008; Nota, Soresi, & Zimmerman, 2004; Winne & Perry, 2000). In this section, components of the self-regulation cycle (forethought, performance, and self-reflection) are reviewed followed by a discussion of interventions used to facilitate self-regulation.

Forethought

During the forethought phase, students' prior beliefs and skills are used to prepare for engaging in a task. People engage in task analysis (goal setting and planning) as well as reviewing motivational beliefs. The motivational beliefs will be revisited throughout all stages of the self-regulation cycle (Schunk & Ertmer, 2000). When students set a goal, they consider what specific outcomes they plan to complete so they can direct their attention towards the task (Locke & Latham, 2002). When students set goals, they are more likely to commit to the goal when the goal is specific as well as realistic (Locke & Latham, 2006; Winne, 2011). After students review a goal, they create a plan for how to complete the specified goal considering numerous factors including: due dates, current knowledge, and task difficulty (Dunlosky & Hertzog, 1998; Son & Kornell, 2009). Son and Kornell (2009) examined students planning intentions for study and found that students will dedicate most study time to difficult tasks, while first completing easier tasks. There may be bias in study intentions such that students expect to study more in duration and across a longer period than actual time spent study (Blasiman, Dunlosky, & Rawson, 2017). Blasiman et al. examined students planned intentions for studying versus a series of recalled reports of study sessions across the semester. They found students overestimated their time they planned to spend studying versus their retrospective reporting of how much time they studied. With both the planning and recall, researchers asked participants to report over a long period, i.e., two weeks for planning and seven days for the recall. Thus, both situations may have instances of bias. To help with this, data regarding plans and study habits should be collected closer to the actual study sessions to limit this issue.

Additionally, during the forethought process, students address self-motivation beliefs (e.g., outcome expectancies and self-efficacy, interest, and goal orientations). Outcome expectancies are beliefs about how performance will be of benefit to the person. Students may study and put more attention towards a course because they believe the skills will help get them a better job after college. However, outcome expectancies depend upon an individual's level of self-efficacy. Bandura (1977, 1986b) described self-efficacy as the perception that a person can complete a task to a given standard. Academic self-efficacy is associated with use of self-regulatory strategies as well as academic performance (Lee, Lee, & Bong, 2014). There is evidence to suggest that higher self-efficacy is associated with setting specific goals that are attainable (Zimmerman, Bandura, & Martinez-Pons, 1992; Zimmerman & Martinez-Pons, 1990). Students may use perceptions of self-efficacy to direct how much time and attention they need to use to complete their goals, even if perceptions of efficacy may not direct students to direct appropriate attention and resources towards studying (i.e., spending more time on studying but using ineffective methods; Zimmerman, et al., 1992). Several factors influence self-efficacy such as previous experiences, social comparison, credible feedback, and physiological factors experienced when engaging in a task (Pajares, 2002; Van Dinther, Dochy, & Segers, 2011).

Another important source of motivation includes students' individual and situational interest (Hidi & Renninger, 2006; Krapp, 2002; Linnenbrink-Garcia et al., 2010). There are numerous conceptualizations of an interest component in the literature, including: intrinsic motivation (Deci & Ryan, 2008; Ryan & Deci, 2000) as well as intrinsic value (Eccles & Wigfield, 2002), but one conceptual similarity involves the directing of attention towards a task (Renninger & Hidi, 2011). Situational interest is a short-term change in affect and attentional resources usually contextually bound by features in the environment (e.g., teachers, features of materials, etc.). On the other hand, an individual interest is a relatively strong disposition towards a particular area. As students have an individual interest in a content area, they may further direct their time and attention towards those tasks across situations (Durik & Harackiewicz, 2007; Lee et al., 2014). They may feel the need to better attend to material in class, as well as to study the material at a deeper level, using techniques designed to help facilitate meaning (Harackiewicz, Barron, Tauer, & Elliot, 2002; Hidi & Harackiewicz, 2000; Mitchell, 1993). For example, rote memorization is a surface level strategy that will not develop meaning in the content, while applying the studied content to a daily life situation helps with establishing perceived value (Hulleman, Godes, Hendricks, & Harackiewicz, 2010; Hulleman & Harackiewicz, 2009).

Additionally, goal orientations are important for students' self-regulatory skills because they are associated with how students direct their attention and choose resources for completing a task, such as what strategies they will use to complete the task (Bouffard, Boisvert, Vezeau, & Larouche, 1995; Hulleman, Durik, Schweigert, & Harackiewicz, 2008; McWhaw, & Abrami, 2001; Pintrich, 2000). Although there are numerous conceptualizations of goal orientations, one common understanding is the separation of performance and mastery orientations (Ames & Archer, 1988; Dweck & Leggett, 1988; Linnenbrink & Pintrich, 2000). A performance goal orientation is where the focus is on achieving some score on a task, while a mastery (or learning) goal orientation concerns goal direction towards learning of content. Another factor is whether students' approach or avoid a given task because of the associated consequences, thus creating three meaningful types of goal orientations: Mastery approach, performance approach, and performance avoidance (Elliot, 1999; Elliot & Church, 1997; Pintrich, 2000). With a performance approach orientation, students are motivated to outperform other people; whereas with a performance avoidance orientation, students are motivated to do just enough to avoid negative consequences. Cellar et al. (2011) examined relationships among goal orientations and self-regulatory behaviors, as well as performance via meta-analysis of 102 reported studies. They found mastery goal orientations were moderately associated with self-monitoring, self-evaluation (e.g., self-rated performance; usefulness of feedback), self-efficacy, self-reactions (e.g., interest), and task performance (e.g., GPA, assessments).

As described previously, there are numerous factors that can contribute to initiating self-regulatory behaviors. As students engage in forethought, their previous experiences and self-beliefs come into play to decide what, how, and how much time is needed to accomplish a task. The aforementioned factors also contribute to other stages of self-regulatory learning (performance and self-reflection), including constant updates as students' progress through given task.

Performance

During the performance phase, people exert self-control of engagement with a task while monitoring how they are performing. First, they determine what strategies they need to use while engaging in the task. For example, while students are studying, they determine if reading over a textbook is sufficient for their purpose, or if they should use a deeper study strategy such as creating a concept map or summarizing material. Weinstein, Husman, and Dierking (2000) discuss various learning strategies that students may use. They distinguished cognitive strategies as strategies that were goal directed, effortful, and intentionally started. Weinstein and Mayer (1986) described a classification system for learning strategies including: rehearsal, elaboration, and organization. Rehearsal is at the lowest end of learning strategies as a repetition of material. Students may write down information the same way as they hear in class, rewrite their notes, or underline information in a textbook. Elaboration is expanding upon the information learned by means of making the content meaningful (e.g., relating to previous information) or creating easier ways to retrieve information (e.g., mnemonic devices). Organization strategies include methods to further connect information together in meaningful ways (e.g., concept maps).

Students may decide to use a combination of content specific study strategies, as well as general study strategies (i.e., strategies they use across disciplines). In self-regulatory learning, strategies are more tailored to a specific discipline (e.g., Hartwig & Dunlosky, 2012) or even the task level (e.g., DiBenedetto & Zimmerman, 2010). There are links between strategy use and with student course grades, both current and future (Nota et al., 2004). For example, Nota et al. examined students reported study strategies and their association with performance in high school and university. They found higher-end cognitive strategies, such as organizing and transforming information, related to both greater high school and university performance. However, there are issues with students using ineffective study strategies (e.g., focusing on seductive details in presentations or rereading the textbook), thus focusing on more time on task at a lower quality of study (Morehead, Rhodes, & DeLozier, 2016). This brings into question how students make judgments on effective time management during study.

Metacognitive monitoring is how students determine if they need to make changes in study strategies and attention. This is in line with Weinstein and Mayer's (1986) conceptualization of comprehension monitoring. They compare how and what they have accomplished, and whether the task has been adequately completed or if more time is needed. Winne (1995, 2001) describes metacognitive monitoring as a crucial feature of self-regulation because monitoring informs goal adherence, changes in planning, and self-judgments. When students exert changes based upon monitoring, they are using metacognitive control. These changes can happen multiple times, and within short time frames, during a single study session.

Self-Reflection

In the self-reflection stage, people further evaluate how they did on the task as well as reflect on why performance was successful or not. Students may have emotional responses to how well or poor a task went and attribute reasons for their successes or failures. These attributions may be adaptive or maladaptive (Weiner, 1986). For example, students may attribute their successes to effective strategy use, which would be viewed as an adaptive attribution. In contrast, students may attribute their lack of understanding to the material being too difficult or an instructor wasting the student's time, which are both maladaptive. This leads to greater insight and planning for the next instance of engaging in the behavior. With adaptive attributions, people are more likely to feel satisfied with their performance and associations with increased engagement. With maladaptive attributions, however, people are more likely to avoid or reduce further engagement to protect from negative feelings (e.g., procrastination, behavioral and cognitive disengagement; Zimmerman & Moylan, 2009).

Measuring Self-Regulation

Given the discussion above, self-regulation is a complex series of tasks and for all the conceptual complexities; there are issues with measuring these complexities. There have been attempts to measure self-regulation in a variety of ways. In this section, I discuss the methods used to measure self-regulation and associated strengths and weaknesses. Each method can contribute to our knowledge of self-regulation, but we need to evaluate how we use these methods as we move forward to make the methods assessable outside of structured experimental settings.

The first way is through single instance self-report measures. Some common examples of self-report measures include the Motivated Strategies for Learning Questionnaire (MSLQ; Pintrich, Smith, Garcia, & McKeachie, 1993), the Learning and Study Strategies Inventory (LASSI; Weinstein, Palmer, & Schulte, 1987), and the Self-Regulated Learning Interview Scale (SRLIS; Zimmerman & Martinez-Pons, 1986, 1988, 1990). With the MSLQ and LASSI, participants respond to examples of self-regulatory skills across a variety of contexts. While this direction lowers participant cost, it may not accurately capture the full nature regarding the complexity of self-regulatory processes (Winne & Perry, 2000). With the SRLIS, participants are engaged in a structured interview in which they solve problems and researchers code responses into self-regulatory behaviors. For example, in Zimmerman and Martinez-Pons (1986), they gave participants hypothetical scenarios and asked about their methods for solving them. This method was further studied in upper elementary through high school gifted and non-gifted students' strategy usage (Zimmerman & Martinez-Pons, 1990). While using the SRLIS sheds insight into participants' planning intentions, it does not provide insight into the monitoring and evaluative states of the self-regulation process.

Instead of measuring self-regulation at a single timepoint, and thus considering self-regulation as a stable trait, there are a variety of methods to measure self-regulation as a context specific event (Cleary, Callan, & Zimmerman, 2012). Some of these methods include using think aloud protocols during a task (Ericsson, 2006), structured diaries completed during a task, or behavioral traces of participant movement during the task (Jamieson-Noel & Winne, 2003; Perry & Winne, 2006; Zhou & Winne, 2012). The similarities among these methods is that participants complete measures of self-regulation while immersed in a task. As of yet, no one method seems best suited for capturing all of self-regulation. For example, researchers using a behavioral trace gain insight about how participants move through a task, but do not directly capture the full thought process of participants (Jamieson-Noel & Winne, 2003; Perry & Winne, 2006; Zhou & Winne, 2012).

There is promise in the use of self-regulatory microanalysis for studying self-regulation (Cleary et al., 2012). In this process, researchers gather behavioral, cognitive, and motivational variables of interest while participants are engaged in the task in a systematic way. Researchers interview participants with questions targeted towards specific steps of the self-regulation loop and monitor performance as participants engage in a specific task. This method has been used in several domains including: athletics (Cleary & Zimmerman, 2001; Kitsantas & Zimmerman, 2002), nursing (Cleary & Sandars, 2011), and academics (DiBenedetto & Zimmerman, 2010; Follmer & Sperling, 2017; Zimmerman & Kitsantas, 1999). The goal is to capture students' thoughts and processes in the moment for various stages of the self-regulatory feedback loop. Students may be asked to set a specific goal and plans for how they will read the journal article (forethought), asked about perceived comprehension and perceptions of efficacy (performance), and attributions for what well or not well during the task (self-reflections). Given the intensive nature of these tasks, they are usually with smaller samples of participants. Furthermore, some of the aforementioned tasks have been completed in a laboratory setting, and participants may not have used the same self-regulatory processes as they would in everyday life.

There is promise in comparing microanalytic tasks to student single instance self-report measures of self-regulatory learning. For example, Follmer and Sperling (2017) found moderate relationships between a reading microanalytic task and MSLQ. By using multiple methods of capturing self-regulation, researchers are able to map a better profile to how students self-regulate in varying situations. With microanalytic approaches, these are time-intensive. There is a need for future research to examine how technology may be beneficial in capturing students' self-regulation in the moment in an ecologically valid way (e.g., using smart phones for self-report and think-aloud reporting during a task).

Based upon the previous research, there are a variety of methods in which self-regulation has been measured. With a large reliance on self-report methods for feasibility sake, there is a need to examine how researchers can best capture participant responses in an ecologically valid way, while not just relying on a single instance report of self-regulation given the contextual nature of the process. One way in which to accomplish these goals are to use the principles of self-regulation microanalysis and use mobile technology to gather data as tasks happen. Utilizing in the moment data collection principles will help address the aforementioned issues.

In the Moment Data Collection

In educational research, researchers traditionally collect data in short-term, single time point measures or in larger-scale longitudinal studies with longer periods of time between each wave of data collection. Researchers use both situations to reduce participant burden by gathering data within one block of time, or a few blocks of time spaced out across time. With these methods, however, there are issues that arise due to potential memory recall and appraisal bias (Kihlstrom, Eich, Sandbrand, & Tobias, 1999; Shiffman et al., 2008). In contrast, there have been advances in the direction of in the moment data collection to capture multiple time points within a shorter period. These methods fall under the window of intensive longitudinal methods such as ecological momentary assessment (EMA; Shiffman et al., 2008) and the experience sampling methodology (ESM; Csikszentmihalyi, Larson, & Prescott, 1977). With this methodology, researchers can better understand participants' daily lives (Shiffman et al., 2008). This methodology allows researchers to study phenomena that are ephemeral and context dependent (e.g., anxiety, interest, study strategies), which is important for educational research (Levine, Lench, & Safer, 2009; Levine, Schmidt, Kang, & Tinti, 2012; Thomas & Diener, 1990). In this portion of the review, I discuss limitations of traditional methods of self-report, methods of collecting data in the moment, and advancements towards using technology with in the moment data collection.

There is not just one methodology designed to collect data in real time. Some of the methods used include: daily diary studies, ESM (Csikszentmihalyi et al., 1977), EMA (Shiffman et al., 2008), and ambulatory monitoring. According to Shiffman et al. (2008), some common themes of in the moment data collection methods include: repeated data collected in real world environments and focus on current or very recent states. By collecting data in their natural environment, researchers aid with increasing ecological validity compared to laboratory or in person data collection. By collecting data closer in time to when the phenomenon of interest happens, researchers help to reduce memory bias during reporting. Methods that recall extensively on retrospective recall are associated with bias, whether it is over or underreporting of a particular behavior (e.g., studying, time on task; Callopy, 1996). Similar reporting bias may be present if asking participants to report about motivational beliefs or affective states over a longer period of time, given how context dependent they are (Goetz, Frenzel, Stoeger, & Hall, 2010; Ketonen, Dietrich, Moeller, Salmela-Aro, & Lonka, 2018).

There are various types of prompting schedules to capture the data closer to the moment. With event related prompting, participants initiate and respond to a series of questions as they engage in a particular activity or emotion (e.g., measuring perceived competence in solving mathematics problems while students are solving mathematics problems). With interval prompting, participants respond to a series of questions at a particular period (e.g., every three hours; daily diary). For example, Ketonen et al. (2018) examined student academic emotions across a day with prompts every three hours. With signal contingent prompting, participants respond to questions at random times through the day. There may be adjustments to signal-contingent to fit within researcher constraints. For example, participants may receive three prompts a day, but each prompt is restricted to happen within a particular time of the day (morning, afternoon, and evening). Finally, there have been advances to incorporate a location or device-based prompting. With this prompting, a participant's devices will initiate prompts if he/she is near a location in where researchers want to gather data.

There are limitations associated with using one type of prompting during a research study. With only using event-based prompting, there may be wide variability in the number of events for each participant. Researchers can see details surrounding an event; however, they do not get information about participant behavior outside of the event. With signal-contingent prompting, researchers gather data about how variables change across time, but some variables may change specifically when engaging in a specific task. It is advantageous to combine prompting types in a study to view a phenomenon as it is happening (event-based) as well as how participants respond across multiple situations at varying times (signal-contingent).

When using event-based prompting, there have been further questions regarding participant compliance, particularly with using paper and pencil (Gable, Reis, & Elliot, 2000; Stone, Shiffman, Schwartz, Broderick, & Hufford, 2003). When using technology, researchers help reduce the doubts of compliance regarding backfilling of responses given the ability to apply time stamps to participant data. Green, Rafaeli, Bolger, Shrout, and Reis (2006) found that providing clearer instruction (e.g., what constitutes a specific event) and showing participants the importance of completing reports when directed helps reduce discrepancies between technology and paper and pencil. Technology may afford better compliance still given a lower burden of carrying digital device vs. an extra diary. Additionally, discrepancies with compliance may still exist regarding non-response (i.e., a participant failing to initiate a session as described by the researcher) when only capturing event-related data. By using signal-contingent prompting in conjunction with event-related prompting, researchers can ask compliance checks to see if participants failed to initiate event-related sessions. For example, for studying behaviors, researchers could ask if participants had studied since the last time they were prompted. By selecting yes, researchers can view the user-initiated data to see if there was a study session prior to when the signal was sent to the participant. If there was not, researchers have evidence of a compliance issue.

For educational research that fits within in the moment data collection, ESM based approaches constitute a large portion. Duck, Williams, and Phillips (2016) found that 43 % of reviewed articles reported some variant of the methods described by Csikszentmihalyi et al. (1977). With ESM prompting, participants receive prompts in a variety of ways including: wristwatches (Hunter & Csikszentmihalyi, 2003; Rathunde & Csikszentmihalyi, 2005), pager/beeper (e.g., Rathunde & Csikszentmihalyi, 2005) and PDAs (e.g., Goetz et al., 2010; Nett, Goetz, & Hall, 2011). With the aforementioned studies, participants would respond to a paper form when prompted. Educational researchers are starting to use participants' smart phones for EMA reporting and data collection (e.g., Dietrich, Viljaranta, Moeller, & Kracke, 2017; Ketonen et al., 2018). This is more convenient for participants and beneficial for researcher burden.

In the Moment Interventions

In addition to using in the moment data collection to assess context specific phenomenon, there have been advances to develop interventions to modify participant behavior in the moment. These more novel ecological momentary interventions (EMI; Heron & Smyth, 2010) are designed to incorporate prompts to help change a target behavior over time. Nahum-Shani et al. (2017) describe several factors that make up a highly customizable form of an EMI: The just in time adaptive intervention (JITAI). Component of a JITAI include the decision points (i.e., when prompts should be sent to participants) and associated decision rules. Intervening prompts may be provided to individuals through similar means as EMA prompts, which include interval, by user-imitated request, or based upon participants' prior responses (Nahum-Shani et al., 2017). Another facet of EMI and JITAI includes what materials are delivered to participants (intervention options). There could be a series of intervention stimuli sent to participants in which participants receive the same materials in the same order, or the materials may be customized based upon a participant's prior information or response (tailoring variables). For example, participants may actively report that they have not studied in the past 24 hours, and thus are sent a prompt with information regarding effective study habits or asked to set a study goal for the next 24 hours.

There are several possible designs for EMIs. Participants may serve as their own baseline in an assessment-only EMA before moving into an intervention phase.

Additionally, there may be multiple groups to investigate between group differences in the intervention versus those in an assessment-only condition. For example, Witkiewitz et al. (2014) evaluated participants drinking and smoking behaviors across three conditions (i.e., a pre-post only, pre-post with EMA, and pre-post with EMI). These methods are starting to be utilized in clinical and health settings (Nahum-Shani et al., 2017; Pramana, Parmanto, Kendall, & Silk, 2014), and more slowly being adopted in educational settings (e.g., Ketonen et al., 2018). With Ketonen et al. (2018), they were interested in student goal setting and associated academic emotions throughout the day. Even though they were assessing how students spend time at the beginning of the day by writing down specific goals, they were intervening in student behavior by having them set goals. With this in mind, it seems reasonable to further incorporate in the moment interventions and with academic tasks (e.g., facilitating the use of self-regulatory strategies).

Current Study

The overarching objective of this dissertation was to examine the implementation and feasibility of a self-regulation intervention delivered in the moment. With the context dependent nature of self-regulatory processes, I used a smartphone application-based method of monitoring student use of study skills and self-regulation across a portion of an academic semester. For this study there was an assessment-only and intervention group, which allowed me to examine different experiential changes in academic motivation and emotions across the study for these two groups. In the intervention condition, I had students set specific goals for study sessions, they received examples of specific study strategies, and were asked to plan out daily time allotments for studying at the end of the prior day as well as re-examine the allotments at the beginning of the current day.

During the study sessions, I employed principles of self-regulatory microanalysis (Cleary, 2011; Cleary et al., 2012), to explore differences in the reporting of quantity and quality of study habits across time.

CHAPTER III

METHODOLOGY

The purpose of this dissertation was two-fold. The first was to examine the feasibility of using multiple types of prompting schedules (researcher-generated and user-generated) to investigate academic self-regulatory processes, emotions, perceptions of competence, and utilization of study strategies in the moment. The second was to examine whether implementing a self-regulatory intervention regarding specific goal setting and presenting examples of study strategies is associated with more consistent study time, as well as more stable academic motivation and motives. I address the purposes of the dissertation in the journal articles presented in Chapters IV and V.

This quasi-experimental study was a two-group, randomized, intensive longitudinal design with a baseline appointment. Participants were assigned to one of two groups, intervention and assessment-only, prior to their appointment. In this design, participants were prompted three times a day for a two-week period. Additionally, participants were trained to initiate a prompt anytime they begin a study session, and they received a researcher prompt thirty minutes after initiating a study session.

Participants

Participants included 49 undergraduate students (63.3% female, average age = 20.20 years, *SD* = 3.79 years) enrolled at a public comprehensive university in the western United States (acceptance rate 90%). The participants were majority freshmen (63.3%) and Caucasian (79.6%; 18.4% identified as Caucasian including Latino). There were a diverse set of majors in the sample including: Psychology (n = 10), Sports and Exercise Science (n = 6) and Business (n = 5). Approximately one quarter of participants in the sample (*n* = 13) met the criteria for academic probation (cumulative GPA less than 2.0). For eligibility, students had to be: over 18 years old, enrolled as an undergraduate student at the university of interest, and have a smartphone capable of downloading the application used in the study.

Materials

Demographics. Participants' gender, age, race/ethnicity, year at university, major/minor, current number of credits earned and enrolled, SES (parents' level of education, past levels of family income); hours spent working, and high school GPA were collected. Participants completed all demographics during the baseline appointment.

Academic records. Participants granted permission (FERPA release) to pull records for standardized test results (ACT/SAT) as well as high school GPA, cumulative and semester GPA at the end of the semester in which they participated. Additionally, I collected previous semester GPA and number of hours attempted/earned. Finally, I collected participants current class schedule at the baseline appointment.

Reading speed. Reading speed was assessed using the Nelson Denny reading speed task (Brown, Fishco, & Hanna, 1993). Participants read a passage for one minute and indicate the line in which they completed at the end of the minute. The number along the edge of the passage indicates words per minute reading speed. This measure was used as a control for the microanalytic task, which was a reading-based task. In the current sample, the most common reported reading speed was 195 with a range of 106 to 364.

Microanalytic task. Self-regulated learning was first assessed via a reading based self-regulated microanalytic task. The text for this task came from the Nelson Denny reading task (Brown et al., 1993). Questions were based upon a microanalytic procedure used by Follmer and Sperling (2017). The research assistant asked participants three questions before reading a passage for forethought (e.g., Do you have any particular plans for how to read this passage?). After reading the passage but before an assessment, participants responded to two questions about performance (e.g., How well did you understand the passage?). Participants then completed an eight-item assessment testing reading comprehension of the passage. After the assessment, participants responded to three questions assessing performance and self-reflection (e.g., Why do you think you may have missed some of the items?). The research assistant made observations of participants behaviors and vocalizations with a behavioral checklist (Appendix D).

Study habits. Study habits at baseline were assessed using a study strategy measure compiled by Morehead et al. (2016). There are 13 questions to capture different aspects of how participants study. Each question has different force-choice options. The measure is used in a descriptive nature over creating composite scores. Example items include “When you study do you typically read a textbook/article/other source more than once?”, “Which of the following best captures how you study?”, and “How do you decide what to study next?” There is evidence of consistency among Morehead et al. based on this measure and with other studies (Hartwig & Dunlosky, 2012; Kornell & Bjork, 2007). An additional question was asked if participants viewed a difference between studying and completing schoolwork and why for their aforementioned response.

Motivated Strategies for Learning Questionnaire (MSLQ; Pintrich et al., 1993). The MSLQ contains 15 subscales designed to measure various motivation orientations and learning strategies. The MSLQ is measured on a 1 (*Not at all true of me*) to 7 (*Very true of me*) rating scale. Based upon Phillips, Phillips, Lalonde, and Dykema (2014), items were adjusted for all courses instead of a specific course. Some example items include "When I study for my classes, I pull together information from different sources, such as lectures, readings, and discussions" and "the most satisfying thing for me in my courses is trying to understand the content as thoroughly as possible." Credé and L. Phillips (2011) examined the utility of the various MSLQ subscales in predicting grades via meta-analysis of 67 independent samples. They found overall support for the factor structure of the MSLQ. They additionally found weak to moderate relationships among the following subscales with class grades and GPA: effort regulation, time and study environment, and self-efficacy. In the current sample, I utilized the metacognitive self-regulation subscale ($\alpha = .71$).

Brief Self-Control Scale (BSCS; Tangney, Baumeister, & Boone, 2004). The BCS contains 13 items designed to measure individual differences in self-control. Items are on a 1 (*Not like me at all*) to 5 (*Very much like me*) rating scale. An example item is "I am able to work effectively toward long-term goals." This measure was used to assess baseline perceptions of self-control and as a control in statistical models for study adherence. In the current sample, there was some evidence of internal consistency ($\alpha = .66$).

Achievement Emotion Questionnaire (AEQ; Pekrun, Goetz, Frenzel, Barchfeld, & Perry, 2011). The AEQ is designed to assess academic emotions (enjoyment, hope, pride, relief, anger, anxiety, shame, hopelessness, and boredom) towards class, studying, and assessment. For the purposes of this investigation, I used the questions tailored for studying, and used the anxiety subscale for analyses ($\alpha = .90$). There are questions specific to before studying (e.g., because I get so upset over the amount of material, I don't even want to begin studying), during studying (e.g., "while studying I feel like distracting myself in order to reduce my anxiety"), and after studying (e.g., "I am so happy about the progress I made that I am motivated to continue studying"), which fit well within the framework of self-regulation I used.

Procedures

This study consisted of two parts: 1) a baseline face-to-face appointment and 2) a two-week smartphone assessment. For recruitment, I utilized a variety of methods (e.g., mass emails sent to student mailing lists, in-class and email recruitment messages sent to instructors, and the psychology research pool).

Prior to when participants arrived for their appointment, they were assigned to the intervention or assessment-only (control) condition in an alternating order to balance on condition. In the face-to-face baseline appointment, participants first acknowledged informed consent and signed a disclosure of academic records (FERPA release). After verifying academic records (e.g., GPA, number of hours completed/attempted, standardized scores), participants completed a microanalytic reading task with the research assistant. The research assistant asked questions related to self-regulation before, during, and after the reading task. Next, participants answered questions in a semi-structured interview format about study strategies typically used. The rest of the measures were answered by the participant on the computer in the lab. At the end of the baseline appointment, participants downloaded the Reallife Exp app (www.lifedatacorp.com) for the EMA/EMI. The research assistant trained participants on the types of questions they received as well as when to initiate prompts for study sessions. Participants had up to one-hour to complete the signal-contingent researcher-generated prompts (described below). Participants were instructed to complete the signal-contingent researcher-generated prompts as soon as they received said prompts.

Ecological Momentary Assessment/
Intervention Protocol

The EMI protocol was for two-weeks (see Figure 1). There were two types of prompts used during the study: randomly scheduled signal contingent researcher-generated prompts (RGP), and user-initiated event-related study session prompts (described below in detail). Following the two-week assessment period, participants returned to meet with a research assistant for compensation. Participants received up to $40 in gift cards for participating in the study. Participants from the psychology research pool received 8 research credits for participating. If they completed over 50% of the prompts, they received an additional $20 gift card. For participants not from the psychology research pool, they received a $30 gift card for participating in the study and an additional $10 gift card if they completed over 50% of the prompts.

Researcher-generated prompts. Participants were signaled via application three times per day with one prompt falling within each of the following strata (8:00 a.m. – 12:20 p.m., 12:30 p.m. – 4:50 p.m., and 5:00 p.m. – 10:00 p.m.). There were four randomized prompting schedules for the RGPs and they were utilized in both intervention and assessment-only conditions. Participants' schedules were preprogramed prior to their baseline appointment. Regardless of condition, participants were asked about the main activity they were doing when prompted. Next, participants were asked whether they have studied since the last time prompted (both in a yes/no and an amount of time format). Participants were also asked about time completing school work. Additionally, participants were asked to rate their academic motivation. Finally, participants were asked to rate various academic emotions at that moment using a modified version of the PANAS-X (See Ketonen et al., 2018 for modified version). For the last prompt of the day, participants were asked about how much time overall did they spend studying for the day as well as class attendance (i.e., whether they missed class, if so how many and which classes) as well as if they had an assignment or an assessment that day. For the intervention condition, participants were asked at the beginning of the day to set a goal for how much time they were planning on studying for the day, and to specify for which classes they planned on studying. At the end of the day, they were asked to identify how much time they planned on studying the next day as well as set a goal for the next day studying.

User-initiated sessions. When participants initiated a study session in the application, participants were first asked to select a course they were primarily going to study for in the session and to direct their responses with respect to that course. Participants in the assessment only condition were asked if they had a goal for the study session, whereas those in the intervention condition were instructed to set a specific goal for the study session. Participants then answered questions related to how much time they planned to study, whether they had an assessment or assignment within the next two days (separate questions), as well as academic emotions related to starting to study. Participants were also asked about their study location. Finally, for the intervention condition, participants were presented one of five study strategies in which participants were asked to incorporate into their study session (self-quizzing, peer teaching, finding relevance to personal experience, connecting concepts, and summarizing information).

Follow-up yoked researcher-generated prompts. At the thirty-minute mark of a study session, participants receive questions regarding whether or not they have finished studying, their perceptions of goal attainment, why they respond a particular way to reaching a goal (attributions for attainment), as well as academic emotions relating to the past thirty minutes of studying. Finally, participants are asked about the strategies they used during their study session.

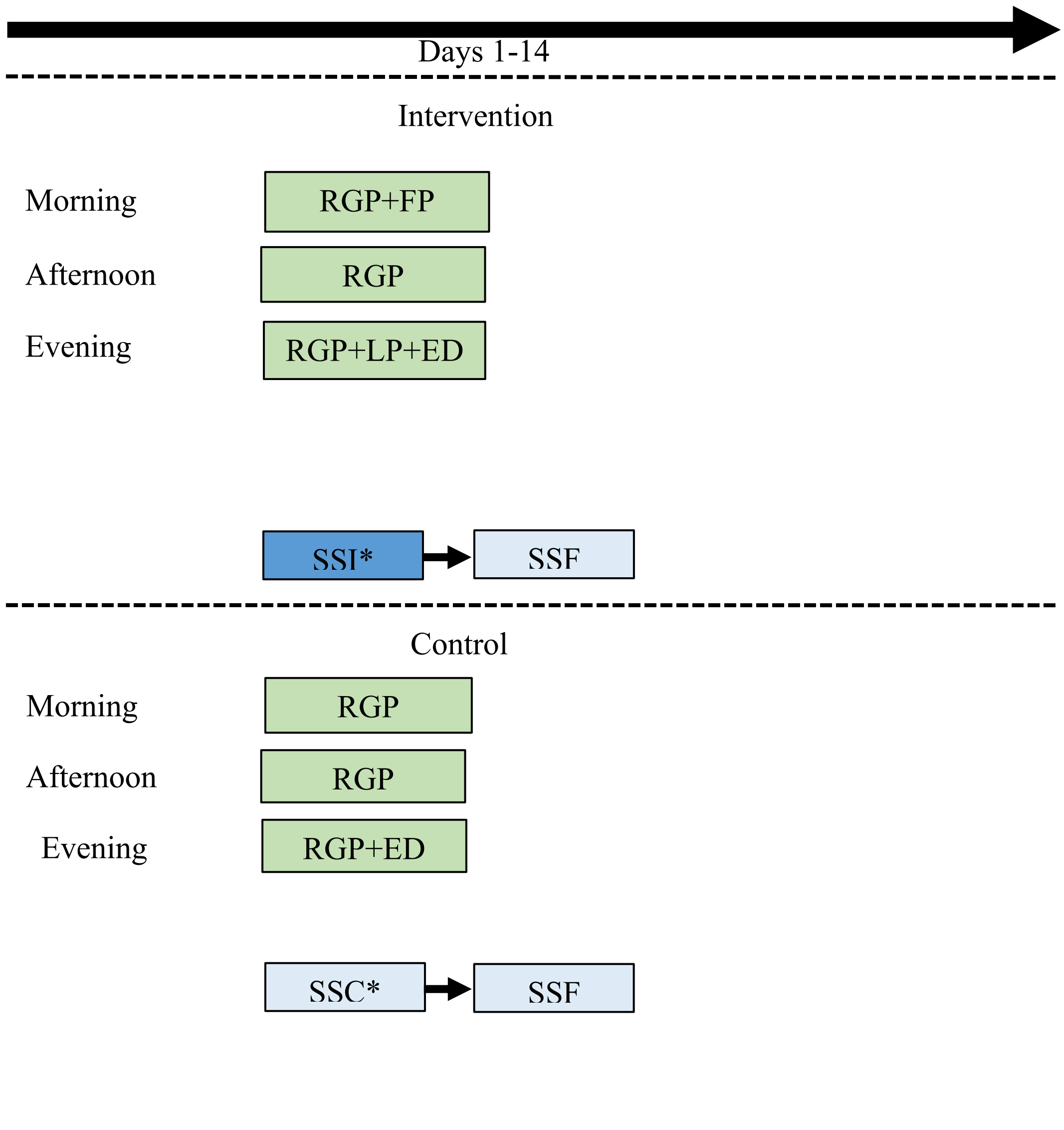

Figure 1. Ecological Momentary Assessment/Ecological Momentary Intervention procedures for prompting. RGP = Research generated prompt; SSC = Study session (control); SSF = Study session follow-up; SSI = Study-session intervention; FP = First prompt of the day for intervention; LP = Last prompt of the day for intervention; * = Participant starts prompt when needed.

Data Analyses

The research questions I addressed are presented below along with the analyses used to address them:

Research Question One

Q1 What factors relate to response rates (e.g., time in study, weekday vs. weekend, and proximity to class time)?

I examined signal-contingent RGP response rates in two ways: the probability of non-response, as well as modeling participants total number of responses. For the probability of non-response, I used a hierarchical logistic model accounting for cumGPA, BSC, time in the study, weekend vs. weekday, and week in the study (week 1 and week 2). For total number of signal-contingent RGP responses, I used a count regression with a Poisson distribution for aggregated EMA response variables including: average academic motivation, average academic anxiety, average academic boredom, and total time studying across the 14 day-period.

Research Question Two

Q2 Are participants compliant to instructions regarding reporting of study sessions for user-initiated prompts?

To examine compliance to instructions, I first looked at number of reported instances of studying in the signal-contingent RGP prompts (i.e., reports of studying since the last time a researcher prompted them) compared to number of user-initiated study sessions (i.e., when participants started a study session in the application). I calculated a discrepancy score (UI-RGP) between the two reports of studying where a negative number indicates they reported more instances of studying (via signal-contingent RGP) than was user-initiated study sessions in the application, indicating a lack of compliance.

Research Question Three

> Q3 Are there discrepancies among reporting of studying since last prompt (yes/no) and how much time spent studying since last prompt (hh:mm)?

To address the discrepancy among time spent studying and whether or not participants studied (both reported during signal-contingent RGP sessions), I initially examined a contingency table with chi-square with studying (yes/no) and time study (0 or above zero). If participants were responding accurately between the two questions, I would expect higher counts in participants reporting zero time when not studying, and higher non-zero times when reporting studying. I compared differences in the counts for the contingency table via chi square analysis.

Research Question Four

> Q4 Are there differences in reported daily study time between the intervention and assessment only conditions?
>
> > Q4a For the intervention condition, are there differences in planned versus reported end of day study times?

To address Q4, I used EMA end of day reported study time as the outcome while controlling for baseline reports of participant cumGPA, MSLQ self-regulation, and EMA daily average academic motivation. For Q4a, I examined the relationship between EMA daily planned vs reported end of day study time, while controlling for baseline report of MSLQ self-regulation, and EMA daily average academic motivation.

Research Question Five

> Q5 Are there group differences (intervention vs. assessment-only) in the relationship among academic motivation and positive and negative emotions when examined over time?

To address relationships among academic motivation and emotions, a series of linear mixed models were fit using R packages “lme4” and “lmerTest” for approximate p-values (Bates, Mächler, Bolker, & Walker, 2014; Kuznetsova, Brockhoff, & Christensen, 2017). I modeled the relationships among EMA academic motivation and emotions in two ways: As a relationship within the same moment (same-moment models), as well as the relationship among academic emotions and motivation at the next time point (lagged models). For these models, I included time point specific positive emotions (Interest, Determined) and negative emotions (Anxiety, Boredom), as well as condition (intervention vs. assessment-only). All variables used in these models came from signal-contingent RGP sessions.

Research Question Six

Q6 Does academic motivation and emotions relate to reports of study engagement? Are these relationships different between the intervention and assessment-only conditions?

To address whether motivation and emotions are related to reports of study engagement, a generalized mixed model was fit. I used report of studying as the outcome of interest from the signal-contingent RGP. Both EMA variables, academic motivation and emotions used in these models were time-dependent covariates, so I created a person level average and deviations from the person level average to examine the relationships across time. I controlled for baseline cumGPA, as well as whether prompts were weekday vs. weekend, and participants’ condition (intervention vs. assessment-only).

Research Question Seven

Q7 Are there differences in the number of initiated study sessions between intervention and assessment only conditions? What about number of completed follow-up sessions?

To address differences in number of study sessions, I aggregated total number of completed user-initiated study session responses (i.e., the number of study sessions participants started in the application) as well as follow-up yoked sessions for each participant (i.e., the prompts that were sent 30 minutes after each started study session). Given the nature of the outcome being counts, a Poisson distribution was used. In this model, I controlled for baseline cumGPA, MSLQ self-regulation, BCS, and EMA aggregates of total time spent studying, study related anxiety and average academic motivation.

CHAPTER IV

FEASIBILITY OF USING MULTIPLE TYPES OF PROMPTING WITHIN AN EDUCATIONAL FOCUSED ECOLOGICAL MOMENTARY INTERVENTION

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Contribution of Authors and Co-Authors

Manuscript in Chapter IV

Author: Kerry D. Duck

Contributions: Conceived the study topic, developed and implemented the study design. Generated and analyzed data. Wrote first draft of the manuscript.

Co-Author: Michael M. Phillips, Ph.D.

Contributions: Helped conceive and implement the study design. Provided feedback on methodological considerations as well as early drafts of the manuscript.

Abstract

In the educational research community, there has been an increase in the number of studies investigating in the moment data collection approaches. With this promise, there is a need to investigate the feasibility of using in the moment methods to extract their full potential. In the current study, we examined the feasibility of using multiple types of prompting (user-initiated and researcher-generated) for participant response rates and compliance to instruction. Participants included 49 undergraduate students at a medium-sized university in the United States. Participants completed a baseline appointment and 14 consecutive days of data collection with three researcher-generated prompts per day as well as various user-initiated prompts. Results indicate low response rates across the study for signal-contingent prompts with participant baseline self-control predicting the missingness of responses over the 14-day period. Also, we found evidence of non-compliance issues for the user-initiated sessions, both in participants initiating prompts when engaged in the target behavior, and with discrepancies in responding to similar questions regarding the target behavior in the researcher-generated prompts. Further research is needed to examine ways to incorporate both types of prompting within an educational environment to help reduce bias in capturing data in the moment.

Keywords: ecological momentary assessment and intervention, missing data, response rates, compliance, educational environments

Introduction

In educational research, researchers traditionally collect data in short-term, single time point measures or in larger-scale longitudinal studies with longer periods of time between each wave of data collection (e.g., weeks, months, or years). Researchers use both situations to reduce participant burden by gathering data within one block of time, or a few blocks of time spaced out. With these methods, however, there are issues that arise due to potential memory recall and appraisal bias (i.e., misremembering information or how one felt during an interaction; Kihlstrom et al., 1999; Shiffman et al., 2008). With the advancements of in the moment data collection procedures, researchers are able to capture multiple time points in close succession within a shorter timeframe. These methods fall under the umbrella of intensive longitudinal designs (ILD) or in the moment studies, which have been referred to as ecological momentary assessment (EMA; Shiffman et al., 2008) and experience sampling methodology (ESM; Csikszentmihalyi et al., 1977) but have developed out of different literature bases. Even with advances for in the moment data collection, very few studies in the education literature have begun to use the full affordances of this methodology (e.g., using multiple types of participant prompting to capture behavior, motivation, and motives). The purpose of this study was to investigate the feasibility of using multiple types of prompting within an educational context (e.g., student studying behaviors). We first review the literature regarding in the moment assessment and factors surrounding feasibility (e.g., participant response rates and compliance to researcher instruction), then focus on how to use these methodologies for intervention.

In the Moment Data Collection

Within in the moment studies, researchers can better understand participants' daily lives (Shiffman, et al., 2008) and study phenomena that are ephemeral and context dependent (e.g., anxiety, interest, study strategies), which is important for educational research (Levine et al., 2009; Levine et al., 2012; Thomas & Diener, 1990). According to Shiffman et al. (2008), some common themes of in the moment data collection methods include repeated data collected in real world environments and a focus on current or very recent states (i.e., feelings, thoughts, behaviors, etc., that occur in very close temporal proximity to a response). By collecting data in their natural environment, researchers aid with increasing ecological validity compared to laboratory or single instance survey data collection. By collecting data closer in time to when the phenomenon of interest happens, researchers help to reduce memory bias during reporting. Methods that rely extensively on retrospective recall are associated with bias, whether it is over or underreporting of a particular behavior (e.g., studying, time on task; Callopy, 1996). Similar reporting bias may be present if asking participants to report about motivational beliefs or affective states over a longer period of time, given how context dependent they are (Goetz et al., 2010; Ketonen et al., 2018). With the wide variety and growing availability for in the moment data collection options to study participants, there is a need to explore how best to leverage the affordances given by in the moment data collection and also acknowledge the current limitations or constraints.

There are various types of prompting schedules to capture data closer to a moment. For event-related prompting, participants initiate and respond to a series of questions as they engage in a particular activity or emotion (e.g., measuring perceived competence in solving mathematics problems while students are solving mathematics problems). The other main category of prompting is generated by the researcher and there are several types of schedule patterns within researcher-generated prompts. With interval prompting, participants respond to a series of questions at a particular period (e.g., every three hours). For example, Ketonen et al. (2018) examined student academic emotions across a day with prompts every three hours. With signal contingent prompting, participants responded to questions at random times throughout the day. One common form of in the moment data collection within educational literature is based upon ESM where participants report eight times a day across a successive period of seven days (although this pattern was not directly specified in Csikszentmihalyi et al., 1977 but many reference this article). There may be adjustments to signal-contingent to fit within researcher constraints. For example, participants may receive three prompts a day, but each prompt is restricted to happen within a particular time of the day (morning, afternoon, and evening) or even within a particular event (e.g., within a given class; Bieg et al., 2017; Dietrich et al., 2017). Further, researchers may specify prompts will not occur within a certain period of time since the last prompt (Beymer, Rosenberg, Schmidt, & Naftzger, 2018; Dietrich et al., 2017). For example, Beymer et al. (2018) specified that participants were to be prompted four times a day, but no two prompts could occur within 15 minutes of the previous prompt. Finally, there have been recent advances to incorporate location or device-based prompting (Pejovic, Lathia, Mascolo, & Musolesi, 2016). With this type, a participant's devices will initiate prompts if he/she is near a location in where researchers want to gather data (e.g., while at the recreation center on campus) or the device picks up certain situational conditions (e.g., low light settings, decibels over a certain range).

There are limitations associated with using one type of prompting during a research study. With only using event-based prompts, the researcher relies on the participant to initiate a response and there may be wide variability in the number of events for each participant and the associated time lapses between events. Researchers can see details surrounding an event; however, they do not get information about participant behavior outside of the event. For example, it would not be possible to examine a participant's affect leading up to an event. With signal-contingent prompting, researchers gather data about how behaviors, feelings, and thoughts change across time or their temporal relation to each other, but some studied variables may change specifically when directly engaged in a task. For example, academic motivation and emotional states (e.g., academic anxiety) may differ while directly engaged in studying versus not. To address the associated issues described previously, it would be advantageous to examine the combination of prompting types to both view a phenomenon as it is happening (event-based) as well as how participants respond across multiple situations at varying times (signal-contingent). Both event-based and signal-contingent prompting schedules were implemented in the current study.

In the Moment Interventions

In addition to using in the moment data collection to assess context specific phenomenon, there have been advances to develop interventions to modify participant behavior in the moment. These more novel ecological momentary interventions (EMI;

Heron & Smyth, 2010) are designed to incorporate prompts to help change a target behavior over time. Even though EMIs are a more recent development, they have been more commonly utilized in the health-related field comparatively to the area of education. In the health-related research, Nahum-Shani et al. (2017) describe several factors that make up a highly customizable form of an EMI known as just in time adaptive intervention (JITAI). Components of a JITAI include decision points (i.e., when prompts should be sent to participants) and associated decision rules. Intervening prompts may be provided to individuals through similar means as EMA prompts, which include interval, by user-initiated request, or based upon participants' prior responses (Nahum-Shani et al., 2017). Another facet of EMI and JITAI includes what materials are delivered to participants (intervention options). There could be a series of intervention stimuli sent to participants in which participants receive the same materials in the same order, or the materials may be customized based upon a participant's prior information or response (tailoring variables). For example, participants may actively report that they have not studied in the past 24 hours, and thus are sent a prompt with information regarding effective study habits or asked to set a study goal for the next 24 hours.

There are several possible designs for EMIs. Participants may serve as their own control in an assessment-only EMA portion before moving into an intervention phase. For example, participants may spend one-week receiving prompts to respond about current activities in an assessment period (EMA), without presentation of strategies, materials, etc., to change a behavior. Another possibility could be multiple groups that would allow the exploration of between group differences (e.g., between an intervention and assessment-only control condition; varying types of intervention messages; or even groups receiving varying levels or dosage of the intervention). For example, Witkiewitz et al. (2014) evaluated participants drinking and smoking behaviors across three conditions (i.e., a pre-post only, pre-post with EMA, and pre-post with EMI). These methods are starting to be utilized in clinical and health settings (Nahum-Shani et al., 2017; Pramana et al., 2014), and more slowly being adopted in educational settings (e.g., Ketonen et al., 2018). With Ketonen et al. (2018), they were interested in student goal setting and associated academic emotions throughout the day. Even though they were assessing how students spent time at the beginning of the day by writing down specific goals, they were intervening in student behavior by having them set goals. With this in mind, it seems reasonable to further incorporate in the moment interventions while targeting academic tasks and strategies (e.g., facilitating the use of self-regulatory strategies). This provided the context for the current study to investigate the feasibility of utilizing multiple types of prompts to examine methodological issues (i.e., response rates, and compliance to researcher instruction).

Methodological Issues

There are several potential methodological issues within in the moment studies beyond the previously mentioned use of different prompting schedules. One such issue is maintaining higher responses rates. Since participants are responding to multiple prompts within a short period of time, it is important for participants to respond to as many prompts as possible to prevent bias in data collection. In previous literature, there are issues with researchers reporting response rates, or the necessary information to calculate response rates within in the moment studies (Duck et al., 2016). Furthermore, there is evidence to suggest that participant response rates may differ based upon a number of factors, which may influence the generalizability of results. Factors may include weekend vs. weekday, time of the day, and day of data collection, i.e., beginning of the monitoring period vs end of the monitoring period (Phillips et al., 2014). In academic settings, another factor that may influence response rates is whether or not the participant is in class when a prompt is sent, or walking (or driving) to class. Although there are education-related EMA studies where participants respond in class (e.g., Dietrich et al., 2017), the purpose of their study was to monitor in class performance. It is not known whether or not participant response rates will differ when the purpose is not specifically targeted for in class data collection.

An additional, but related issue, involves participants' compliance to researcher instructions, which may be harder to ascertain when using user-initiated (event-related) prompting, particularly when using paper and pencil reports (Gable et al., 2000; Stone et al., 2003). For the purposes of this study, compliance was defined as responding to/or initiating prompts when respondents should have initiated (e.g., when they are studying, participants should initiate a prompt) based on the study instructions provided during the baseline appointment. When using technology, researchers help reduce compliance issues around backfilling of responses given the ability to apply time stamps to participant data. However, issues still exist for user-initiated event-related prompts, for example, with participants missing an event, recording events at a later time period than when they actually occurred, and potential confusion for interpreting whether an event has occurred or not in order to report. Green et al. (2006) found that providing clearer instruction (e.g., what constitutes a specific event) and showing participants the importance of completing reports when directed helps reduce discrepancies between technology and paper and pencil. Technology may afford better compliance given a lower burden of carrying a digital device vs. an extra diary. Additionally, discrepancies with compliance may still exist regarding non-response (i.e., a participant failing to initiate a session when an event happened) when only capturing event-related data. The likelihood of knowing whether or not there are missing data is low with only using event-related data. For example, Xie, Heddy, and Greene (2019) report on using both fixed prompting and event-based prompting of study behaviors. They reported zero missing data using event-based prompting, which is hard to ascertain using only event-related prompting protocols unless the researcher knows a priori when the events will be occurring (e.g., while in a course). By using signal-contingent prompting in conjunction with event-related prompting, researchers can ask compliance checks to see if participants failed to initiate event-related sessions when they were supposed to initiate. For example, for study behaviors, researchers could use signal-contingent prompts to ask whether participants had studied since the last time they were prompted. By selecting yes, researchers can check this against user-initiated event-related data to investigate whether a study session prior to the signal-contingent prompt was initiated. If there was not, researchers have evidence of a compliance issue. Conversely, if participants report they did not study, while there is a user-initiated session, there is also evidence of a compliance issue.

Within previous literature, there have been issues with determining feasibility of using EMA/ESM in published studies within educational contexts due to a lack of reported methodological considerations (e.g., response rates, prompting schedule clarity, compliance to researcher instructions, etc.; Duck et al., 2016). These reporting practices are improving, with researchers providing more information to determine response rates and time to complete prompting (e.g., Ketonen et al., 2018; Xie et al., 2019) but there are still a number of methodological considerations that need to be addressed with in the moment studies (i.e., the feasibility of using both signal-contingent and user-initiated (event-based) prompts to check for participant compliance to researcher instructions).

The Current Study

The main purpose of this investigation was to examine the feasibility of using multiple types of prompting with EMA/EMI within an educational context. Specifically, we were interested in factors related to response rates (for signal-contingent prompts) and compliance to researcher instructions (for user-initiated prompts) and how these might vary between a combined EMA/EMI condition compared to an EMA-only condition. To address these aims, we examined the following questions:

Q1 What factors relate to response rates (e.g., time in study, weekday vs. weekend, proximity to class time, and reminders delivered.)?

Q2 Are participants compliant in reporting of study sessions for user-initiated prompts?

Q3 Are there discrepancies among reporting of studying since last prompt (yes/no) and how much time spent studying since last prompt (hh:mm)?

Methods

Participants and Procedures

Participants included 49 undergraduate students enrolled at a public comprehensive university in the western United States (acceptance rate 90%). The participants were a majority freshman (63.3%), female (63%), and Caucasian (79.6%; 18.4% identified as Caucasian including Latino), with an average age of 20.20 years (*SD* = 3.79; range = 20). There were four participants above the age of 23. There were a diverse set of majors in the sample including Psychology (n = 10), Sports and Exercise Science (n = 6) and Business (n = 5) with other various individual majors. In our sample, the average cumulative GPA was 2.71 (*SD* = 1.03). Approximately one quarter of participants in the sample (*n* = 13) met the criteria for academic probation (cumulative GPA less than 2.0). For eligibility, students had to be over 18 years of age, enrolled as an undergraduate student at the university, and have a smartphone capable of downloading the application used in the study.

Participants were recruited through the psychology department research pool, as well as emails sent to faculty with a request to post an announcement on their course learning management system. Prior to the two-week mobile assessment, participants presented to the lab for a baseline appointment where they completed demographic information, a study strategies interview, and self-report measures regarding academic motivation and motives (described below). They were randomly assigned to an assessment-only or intervention condition prior to their baseline appointment. Ecological momentary assessment data was collection for the study using the mobile smartphone app "RealLife Exp" from LifeData, which is a mobile app designed specifically for EMA data collection on smartphones (lifedatacorp.com). In the current study, participants used their own smartphones and were trained during the baseline appointment on how to use the app, including where to start user-initiated event-related session and the types of questions to expect.

Participants were prompted three times a day during the 14-day assessment period with signal-contingent prompts. They had up to one hour to respond to these prompts sent by the researchers (Researcher-Generated Prompts; RGP). The RGPs were delivered on a random signal-contingent schedule within three defined blocks (8:00-12:20; 12:30-4:50, and 5:00-10:00), with a reminder sent thirty-minutes after the initial signal (see Hektner, Schmidt, & Csikszentmihalyi, 2007 for further discussion of signal-contingent scheduling). Participants had up to one-hour to complete these prompts and were instructed to complete the prompts as soon as they received them, if possible. In addition to the abovementioned RGP schedule, participants were asked to initiate a session in the app (user-initiated) whenever they engaged in studying (any session in which they sat down to prepare for a class that did not result in a direct grade). Participants received a yoked-RGP thirty-minutes after they initiated the study session with follow-up questions concerning their study session.

In this study, there was a possibility of 42 signal-contingent RGPs delivered to all participants, or 2,058 questionnaires overall (42 questionnaires per person for 49 participants). Additionally, participants received yoked-RGPs dependent upon the number of completed user-initiated event-related study sessions (range 0-10 for received yoked-RGPs in the current sample).

Data Sources

Baseline measures. Along with collecting demographic factors (age, gender, major, status in school, transfer status, cumulative GPA, and hours spent working per week), we also collected several self-regulatory measures to use as covariates in our analyses. All of these measures were collected at the baseline appointment. We measured self-control using the Brief Self Control Scale (BSCS; Tangney et al., 2004), which is 13 items on a 1 (*Not like me at all*) to 5 (*Very much like me*) rating scale ($\alpha = .66$). We addressed metacognitive self-regulation for academic tasks with a subscale from the Motivated Strategies for Learning Questionnaire (MSLQ; Pintrich et al., 1993), which contained 12 items on a seven-point rating scale ($\alpha = .71$).

Class schedules. Participants class schedules were collected during the baseline appointment and were used with the signal-contingent RGP data. Researchers used participant class schedules to identify four specific time categories: in class, between consecutive classes, not in class, and class time but skipped. The skipped class reports were coded from those participants who reported skipping a class during the end of day prompt.

Ecological Momentary Assessment/ Ecological Momentary Intervention prompting.

Signal-contingent researcher generated prompts (RGPs). All participants received these prompts three times a day for the 14-day assessment period, for a total possible 42 time points. Regardless of condition, participants were asked about the main activity they were doing when prompted. Next, participants were asked whether they studied since the last time prompted (both in a yes/no and an amount of time format), in addition to rating their academic motivation. Finally, participants were asked to rate various academic emotions at that moment using a modified version of the Positive and Negative Affect Schedule (PANAS; See Ketonen et al., 2018). For the last prompt of the day, participants received additional questions and were asked about how much time overall they spent studying for the day as well as class attendance (i.e., whether they missed class, if so how many and which classes) and if they had an assignment or an assessment that day.

Ecological Momentary Intervention interval researcher generated prompts. For the intervention condition, participants were asked during the first prompt of the day to set a goal for how much time they were planning on studying for the day, and to specify for which classes they planned on studying. During the last prompt of the day, they were asked to set a goal for the next day studying.

User-initiated event-related prompts. When participants were getting ready to study they were instructed to initiate an event-related study session. When initiated, participants received questions that asked them to select a course they were primarily going to study for in the session which would be addressed in follow-up yoked-RGP prompts. Participants in the assessment-only condition were asked if they had a goal for the study session, whereas those in the intervention condition were instructed to set a specific goal for the study session.

Follow-up yoked researcher-generated prompts. After initiating a study session, participants would then receive a yoked-RGP at the thirty-minute mark of a study session. Participants received questions regarding whether or not they had finished studying, their perceptions of goal attainment, why they responded a particular way to reaching a goal (attributions for attainment), as well as academic emotions relating to the past thirty minutes of studying. Finally, participants were asked about the strategies they used during their study session.

Data Analyses

EMA response rates and missingness. Response rates focused on the proportion of responses completed for signal-contingent RGPs over the 14 days (42 possible time points). For each participant, we recorded the total number of prompts sent and the number of prompts in which participants responded. We then calculated response rates by day of the week, week in the study (week 1 vs. week 2), and weekday vs. weekend. We considered all participant responses within the established response window (1 hour from signal). All models were fit using R.

We examined signal-contingent RGP response rates in two ways: the probability of non-response, as well as modeling participants total number of responses. For the probability of non-response, we used a hierarchical logistic model accounting for baseline cumGPA, BSC, as well as EMA indicators of time in the study (time point 1-42), weekend vs. weekday, and week in the study (week 1 and week 2). For total number of signal-contingent RGP responses, we used aggregated EMA response variables for average academic motivation, average academic anxiety, average academic boredom, and total time studying (in minutes) across the 14 day-period.

Compliance to researcher instructions. For each participants' user-initiated (event-related) and follow-up yoked-RGP prompts, the total number of user-initiated prompts within the two-week data collection period, the number of user-initiated prompts completed, and the number of completed follow-up yoked-RGP prompts were compiled.

To look at compliance to researcher instructions, we examined the number of user-initiated (event-related) sessions (i.e., when participants opened the application to start a study session) compared to the reported number of signal-contingent RGP instances of studying (i.e., stating whether or not they have previously studied when the researcher prompted), as well as signal-contingent reported instances of user-initiated (event-related) sessions (i.e., where participants were asked during the signal contingent prompts whether they had started an user-initiated study session). We calculated a discrepancy score where we compared actual user-initiated started sessions (UI) compared to signal-contingent reports of starting a study session (RGP) for a comparison of (UI-RGP) where a negative number indicates that they reported more instances of reported studying than was user-initiated, indicating a lack of compliance.

Discrepancy among studying questions. We additionally examined two signal-contingent questions regarding studying behaviors (i.e., whether they studied since the last prompt compared to how much time they had studied) and potential discrepancies between participants' responses to the two aforementioned questions (e.g., reporting not studying and reporting a positive time spent studying).

To address the discrepancy signal-contingent reports between time spent studying and whether or not participants reported engaging in studying, we initially examined a contingency table with chi-square with studying (yes/no) and time studied (0 or above zero). If participants were responding accurately between the two prompts (at the same time period), we would expect higher counts in participants reporting zero time when they had not studied since the last prompt (a “no” response), and higher non-zero times when reporting studying (a “yes” response). We compared differences in the counts for the contingency table via chi square analysis.

Results

Research Question One

Q1 What factors relate to response rates (e.g., time in study, weekday vs. weekend, proximity to class time, and reminders delivered.)?

For the signal-contingent RGPs, a total of 2,058 total prompts were sent over the 14 days, and there were 1,345 responses resulting in an overall response rate of 65.40%. The overall response rate did not differ by intervention or control conditions on average, t (47) = 0.35, p = .73. This aforementioned similarity between the conditions continued with respect to day of the week, day in the study, and week one versus week two on average, with no differences being found.

We examined response rates throughout the study. One participant responded to every signal-contingent RGP, and half of participants had a response rate of 75 percent or better. With regard to day in study (i.e., day 1, day 2…day 14), response rates ranged from 61.22% to 71.43%. Average response rates for week 1 were 66.28% and week 2 were 64.63%. For day of the week, response rates were the highest on Thursday (70.07%) and lowest on Saturday (56.43%). With regards to time of day, participants responded on average to 62.97% during the first time point (morning), 65.45% during the second time point (afternoon), and 67.64% during the third time point (late afternoon/evening), suggesting a slight increase in responding across the day. Furthermore, response rates were lower on the weekend compared to the weekdays. See Tables 1 and 2 for further breakdown of response rates by condition.

Table 1

Average Response Rates by Day of Week and Week in Study

	Overall (n=49)	**Assessment-Only (n=25)**	**Intervention (n=24)**
	***M* (SD)**	***M* (SD)**	***M* (SD)**
Monday	69.39 (31.43)	71.33 (31.37)	67.36 (32.26)
Tuesday	66.67 (34.36)	70.00 (31.91)	63.19 (37.10)
Wednesday	69.05 (33.33)	70.67 (32.73)	67.36 (34.57)
Thursday	70.07 (32.80)	69.33 (33.57)	70.83 (32.69)
Friday	62.93 (34.24)	64.57 (32.74)	61.11 (36.34)
Saturday	56.43 (32.78)	58.00 (33.72)	54.86 (32.41)
Sunday	63.61 (29.79)	64.67 (32.39)	62.50 (27.47)
Week 1	66.28 (28.34)	66.29 (29.80)	66.29 (27.37)
Week 2	64.63 (31.12)	67.62 (30.34)	61.51 (32.26)

Table 2

Average Response Rates by Day in Study

	Overall (n=49)	**Assessment-Only (n=25)**	**Intervention (n=24)**
	***M* (SD)**	***M* (SD)**	***M* (SD)**
Day 1	70.07 (35.52)	73.33 (36.00)	66.67 (35.44)
Day 2	67.35 (32.98)	68.00 (31.15)	66.67 (35.44)
Day 3	71.43 (36.64)	66.67 (39.67)	76.39 (33.30)
Day 4	64.63 (35.62)	66.67 (37.27)	62.50 (34.49)
Day 5	61.90 (37.27)	60.00 (39.67)	63.89 (35.33)
Day 6	61.22 (38.70)	60.00 (39.67)	62.50 (38.46)
Day 7	67.35 (37.57)	69.33 (38.39)	65.28 (37.40)
Day 8	66.67 (39.09)	66.67 (38.49)	66.67 (40.53)
Day 9	65.63 (38.13)	66.67 (37.27)	62.60 (39.70)
Day 10	68.03 (37.86)	68.00 (36.62)	68.06 (39.90)
Day 11	61.22 (39.29)	69.33 (39.58)	52.78 (37.96)
Day 12	61.22 (39.29)	62.67 (38.87)	59.72 (40.50)
Day 13	63.95 (37.17)	69.33 (35.90)	58.33 (38.39)
Day 14	66.67 (35.36)	70.67 (32.38)	62.50 (38.46)

For those prompts delivered during the academic week (number of prompts = 1470; response rate = 67.62%), 238 of those prompts were delivered within scheduled class times. Given the sparse instances of participants being prompted between consecutive classes (number of occurrences = 5), responses from between consecutive classes and within thirty minutes of classes were collapsed within the class time variable as “class or in-transit to class” resulting in a total of 368 instances of “class or in-transit to class.” Additionally, there were 33 instances where participants skipped class, and were categorized with the not-in-class category (total of 1102 instances). Participants responded to 68.75 percent of prompts delivered during *class or in-transit to class* compared to 67.15 percent of prompts delivered while not during class times.

In addition to the descriptive statistics presented above, we examined the probability of non-response in signal-contingent RGPs with a hierarchical logistic regression accounting for cumGPA, self-control (BSC), baseline study anxiety, time in the study (out of the 14 days), weekend vs. weekday, and week in the study. Given the repeated nature of the data, we added a random effect for time to account for repeated observations. In addition to parameter estimates, we present the odds-ratio (OR) for each of the parameters, which represents the odds of whether or not an event will occur (e.g., responding). Based upon the model, higher baseline self-control was associated with an increased probability of responding, (B = 0.09, OR = 1.09, $p = .045$). Additionally, there was a lower probability of responding on the weekend, (B = -0.50, OR = 0.61, $p < .05$), as well as across the course of the study (B = -0.02, OR = 0.98, $p = .02$). Next, we added class time vs. not to the model to examine probability of missing specifically during the weekdays. This necessitated the removal of the weekday vs. weekend variable from the model, the remaining variables stayed the same as the prior model. Based upon this model, class time was not associated with an increased probability of response; only self-control remained associated with the probability of non-response (B = 0.11, OR = 1.11, $p < .05$).

We further addressed cumulative number of signal-contingent responses (per participant) with a count regression using aggregated EMA response variables for average academic motivation, average academic anxiety, average academic boredom, and total time studying (in hours) across the 14 day-period. Within our sample, the range of completed signal-contingent prompts was 39 (3 to 42 completed prompts). See Figure 2 for distribution of response counts. The median number of completed signal-contingent prompts was 32. In the model, aggregated EMA for average academic motivation (B = -0.06, OR = 0.94, $p < .05$) and average boredom (B = -0.10, OR = 0.91, $p < .05$) were associated with a lower expected count while time spent studying (B = 0.01, OR = 1.01, $p < .05$) was associated with a higher expected count.

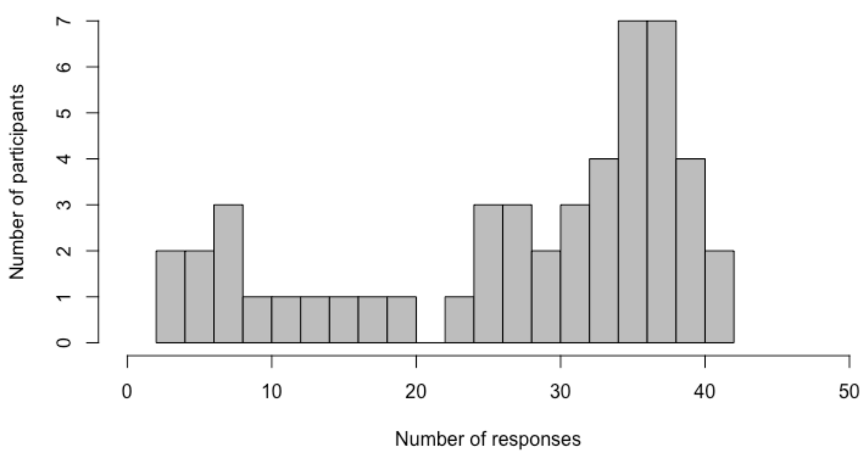

Figure 2. Histogram of total number of signal-contingent responses across participants.

Research Question Two

Q2 Are participants compliant in reporting of study sessions for user-initiated prompts?

To examine compliance to researcher instructions (i.e., initiating user-initiated sessions), we first looked at number of reported instances of studying in the signal-contingent RGP responses compared to actual number of user-initiated event-related study session. We calculated a discrepancy score (UI compared with signal-contingent RGP). It is worth noting that 18 instances of user-initiated study sessions occurred after the established 14-day window had ended, which were removed prior to addressing UI to RPG compliance. On average, participants initiated two more study sessions for UI occurrences than were reported at signal-contingent RGPs (M = 2.28, SD = 3.25) with a range of 22. There was only one instance of an extreme negative score (i.e., where they reported starting more user-initiated sessions in the signal-contingent RGP than they actually user-initiated; score of -12). Additionally, there was one person who only completed three signal-contingent prompts in the study, which would lead to a restriction of range on their possible discrepancy score.

Research Question Three

Q3 Are there discrepancies among reporting of studying since last prompt (yes/no) and how much time spent studying since last prompt (hh:mm)?

Within the signal-contingent RGPs, we asked two questions regarding studying behaviors ("Have you studied since the last time you were prompted?" *Yes/No* and "How much time have you studied since the last time you were prompted?" *in minutes*). We compare these two questions as a validity check on consistent reporting of study behaviors. There were a plurality of responses that were zero (n = 822) and several responses between one and five minutes (n = 147). Across all participants, they reported studying since the last prompt 9.91 percent of the time when participants responded to the signal-contingent RGPs and reported *time spent studying* (that was not zero) 22.50 percent of the time, χ^2 (1) = 395, p < .001. Thus, we compared a contingency table to the aforementioned questions where consistent reporting would be a "no" to studying (coded as zero) and a zero for *time spent studying*, and conversely non-zero responses for *time spent studying* if responding “yes” to studying. We also examined the discrepancies in reporting between these two questions. When participants reported they studied since the last prompt (*yes* response) in the signal-contingent RGPs, they reported zero for *time spent studying* only 2.45%, which may be due to participant error for answering yes on whether or not they have studied. However, when participants reported they did not study since the last prompt (*no* response), they responded with a non-zero study-time 24.42% of the time, suggesting participants are not responding consistently across similar questions regarding studying behaviors (see Table 3 for reported instances of studying and time spent studying).

Table 3

Contingency Table for Reports of Reported Time Spent Studying versus Reported Studying since Last Prompt.

		Time Spent Studying	
		Zero	Non-Zero
Studied Since Last Prompt	Yes	5	199
	No	817	264

Discussion

This was one of the first studies to implement simultaneous use of both user-initiated (event-related) and signal-contingent (researcher-generated) prompting in an educational environment. Based upon our data, we had issues with participants responding across the two-week period, but our response rates did not have sharp drop offs near the end of the study, which can happen with EMA studies. Our overall response rate was approximately 65% with daily reporting averages as low as 50%, with only a slight decrease in the odds of responding across time. These response rates were in line with what Beymer et al. (2018) found, where participants were engaged in doing academic related tasks during a summer camp. The response rates are also in line with Xie et al. (2019) in a college sample of pre-service teachers (approximately 68%). Prior educational based EMA/ESM studies report response rates ranging from 48 to 88 percent (Beymer et al., 2018; Converse, Juarez, & Hennecke, 2019; Dietrich et al., 2017; Fryer, Ainley, & Thompson, 2016; Ketonen et al., 2018). In our study, we had a longer protocol time, but fewer prompts per day than a number of the other studies. Our prompting window did range from 8:00 a.m. to 10:00 p.m. daily for 14 consecutive days compared to more prompts over fewer days, and we did see slightly higher response rates on average over the course of the day. In addition, we also collected data over the weekend and found lower response rates than during the week.

Factors surrounding participants' daily lives may have contributed to lower response rates. Participants were college students with various commitments in and outside of the university setting (e.g., extracurricular activities, work commitments). In the current study, we did not account for participant work or class schedules when designing prompting schedules, which may have led to lower response rates. However, no differences were found between the in-class and out of class response rates in this study. In one way, this is good in terms of participant compliance, but in another it is problematic. The context of this study revolved around examining participants' self-regulation of learning, and by having similar response rates while in class, shows a potential lack of self-regulation in a learning environment (e.g., responding to smartphone messages could distract from paying attention and learning). Additionally, some participants engaged in extracurricular athletics, and this was mentioned during informal feedback as a possibility for participants' missing data. When looking at the probability of non-response, we found that participants' level of self-control was positively associated with a higher likelihood of response. One explanation could be that those who are lower in self-control may not see issues with not responding because they do not view participation as important as the alternative, or they are allocating time to other tasks. Additionally, we found that higher levels of average EMA predictors of boredom and academic motivation were associated with a decrease in the count for responding. Based upon this, those who felt a regular sense of boredom on average maybe were less likely to engage in a task-related to academics (as many were participating via the research participant pool for course credit). On the other hand, those with a higher sense of academic motivation over the course of the study may be more focused on their academic tasks and not disengage to respond to prompts. More research is needed to examine contributions of in the moment and aggregates of motivational constructs when considering response rates.

We also saw evidence of issues with complying to researcher instruction regarding initiating a user-initiated event when it occurred. Overall, we saw only one participant who reported significantly more study sessions in the signal-contingent researcher prompts than what was actually initiated by the participant. We found more instances where participants started an user-initiated session than what were reported on the in the signal-contingent researcher prompts for studying, but this could be due to low response rates for signal-contingent RGPs. We acknowledge that even with time stamps for participant responses, these are still self-report instances of engagement. Further examination is needed regarding when participants initiate sessions relative to their last response to a signal-contingent RGP. Descriptively, we did see instances where participants initiated an event right after receiving a researcher generated signal-contingent prompt, but this was not always the case. The signal-contingent prompt could have served as a reminder to initiate an event-based study session, but there are questions as to whether the data are from an actual study session, or rather a demand characteristic to initiate. One would feel more inclined to trust the data more from those who initiated at times not directly following a signal-contingent prompt as this could be past behavior that is in response to the cue instead of currently being engaged in the behavior at that moment. The other possibility could be that the signal-contingent RGP worked as a reminder that they should be studying more, and the assessments worked to shift behavior, thus resulting in reactivity to the RGPs. Reactivity has been defined as a change in a behavior based upon monitoring said behavior (Kazdin, 1974).

We additionally found a discrepancy in reporting study behaviors within the same signal-contingent RGPs. We found overall that participants who reported not studying since the last prompt also reported time spent studying approximately 22 percent of the time, bringing into question the discrepancy between these two. Participants may have reconsidered what was meant by studying between the two questions, or participants were reminded of studying between the questions. One way to see if there are discrepancies between the two reports of studying in the signal-contingent questions would be to counterbalance the order of the questions in future studies.

Limitations

When discussing the findings, we noted limitations related to response rates that could directly be addressed with the gathered data. This study has a few additional limitations. Factors for issues regarding our lower response rate and compliance to researcher instruction may relate to characteristics of our sample, as well as when data were collected for this study. Additionally, issues may relate to factors outside of participants' control (e.g., working). One factor we did not consider when recruiting for the study was if participants were student athletes. There were instances of participants reporting that they could not user-initiate study sessions or respond to signal-contingent prompting if they were in a study hall period, where technology was not allowed. To address why the time of data collection may influence results, it is important to remember the context of the study. The context of this study involved participants' reporting of study time and strategies. With collecting data in the second half of the semester, participants may not user-initiate study sessions because they were established in study routines and felt confident in their study time allotment. This could lead to lack of group differences in factors such as response rate between our two conditions. Additionally, the majority of the data for this study were collected in the second half of the semester where participants had already established their study routines and were also preparing for the end of the semester. Participants had already completed a number of course assessments and projects, and thus might have felt confident in their time allotment and preparation strategies and this could have explained the lack of difference in response rate between the control and intervention groups. They may have decided which courses they needed to engage and study more for and prioritized those over others where they did not perceive they needed to study. This may have contributed to the lack of intervention versus assessment-only differences in the study. While in the protocol, we asked participants to set daily study goals, they may have not committed to the goals because of a lack of perceived need. Further, approximately 25 percent of the participants completed the research protocol right before finals week, so the participants that completed the EMA protocol in the last two weeks of the regular semester may have not started study preparations for final exams. In future work, it would be best to assess participants' habits across various portions of the semester, to see if the pattern of study changes as the semester ends.

A third limitation is whether participant compensation was enough for participation at a higher rate. Participants were compensated with full course research credit for achieving up to a 50 percent response rate on the signal-contingent researcher-generated prompts (RGPs). Those who achieved over a 50 percent response rate were compensated with an additional $20 gift card. For those not in the participant research pool, they were compensated with a $30 in gift card for completing the baseline appointment and achieving a 50 percent response rate on the two-week EMA protocol. Those responding above 50 percent received an additional $10 gift card. There were no differences in the response rates on average from those in and out of the participant research pool. Factors to consider in future work include differentiating the compensation further tied to participant engagement, given the low response rate and compliance to user-initiated sessions. The burden of participating in an EMA/ESM study tends to be higher than other study protocols and thus the compensation structure might need to be explored in greater depth. Another factor to consider is when participants are compensated. We used an end-of-study compensation strategy, but it may have been more beneficial to use incremental compensation for the monetary compensation (Hall & Nishina, 2019). For example, instead of offering full compensation at the end of the study, offer a smaller amount (e.g., $1 per completed response) at the end of each day. The course research credit option may not be viable as incremental incentivization, because as participants achieve what they need for course credit, they may stop responding to the study prompts. This was based upon some of the informal feedback we received from participants at the end of the study.

Conclusions

Overall, there was support in terms of the feasibility of using signal-contingent and event-based prompting simultaneous in educational settings. We did see some discrepancies in terms of how participants responded to similarly worded questions within the signal contingent prompting. We need to further explore changes in the protocol to help reduce issues with reporting discrepancies as well as to increase participant response rates. This type of in the moment protocol is not widely used, and thus more research is needed on implementation strategies. For the educational context, we might need to consider courses where participants feel they need to study more. Additionally, in future research, we need to consider the use of reminders within signal-contingent prompting to encourage the behavior of interest as well as changing the compensation strategy. Finally, different times of the semester should be taken into consideration to examine potentially different patterns of response rates and compliance.

CHAPTER V

STUDYING IN THE MOMENT: USING SELF-REGULATION AS A FRAMEWORK FOR AN ECOLOGICAL MOMENTARY INTERVENTION

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Contribution of Authors and Co-Authors

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Contributions: Helped conceive and implement the study design. Provided feedback on methodological considerations as well as early drafts of the manuscript.

Abstract

With the continuing issues related to student retention within higher education, there is a need to explore various methods to help students as they progress through university. In the current study, we used an ecological momentary intervention (EMI) surrounding aspects of self-regulation (in particular goal-setting) to monitor student study behaviors, academic motivation, and motives. Participants included 49 undergraduate students at a medium-sized university in the United States. Participants completed a baseline appointment and 14 consecutive days of in the moment data collection with three researcher-generated prompts per day and a various number of user-initiated reports. Results indicate marginal difference in the relationship of academic motivation and emotions within the same moment between a control and intervention group, but no group differences were found in terms of studying, suggesting a lack of treatment effect on study behavior. Baseline factors such as lack of self-regulation and the study strategy of cramming, as well as in the moment reports of anxiety were associated with lower instances of studying. We also found a moderate relationship between planned vs end of day reports of studying. Future directions include examining self-regulatory based interventions in more targeted courses that participants perceive to require higher time commitments.

Keywords: ecological momentary assessment and intervention, self-regulation, goal-setting, academic motivation

Introduction

Retention and persistence to graduation continues to be an issue for institutions of higher education where several factors may contribute to student attrition including financial burden, emotional experiences (e.g., dissatisfaction with the university), and a lack of preparedness and motivation to regulate learning with newly found autonomy (Alarcon & Edwards, 2013). Skills typically taught in first year programs (e.g., self-regulatory skills) may need to be visited and revisited as students' progress to higher level course work as setting specific goals, time-management and self-regulation of learning become even more important (Morisano et al., 2010; Robbins et al., 2004; Zimmerman, 2008).

The purpose of the current study was to examine if there were differences in reported academic motivation, motives, and study times between an intervention based upon self-regulation principles, vs an assessment only condition. For the current study we used an ecological momentary intervention (EMI) while collecting data with ecological momentary assessments (EMA), a form of intensive longitudinal data collection, to explore the use of facets of self-regulation in students' daily lives, and to monitor their academic motivation and motives as well as their academic engagement. We were interested in how student motivation and engagement fluctuated across the day as well as between days. These data were collected across 14 consecutive days via a smartphone app, and included prompts delivered by the researcher (researcher generated prompts), as well as prompts initiated by the participant (user-initiated prompts). The main purpose of this study was to examine a self-regulatory intervention, with an intervention and assessment-only control group, regarding student goal-setting and planning, and the relationship to students' perceived academic motivation, emotions, as well as engagement in academic behaviors (e.g., time spent studying, time spent completing schoolwork). We examined the relationships among academic motivation and emotions in the moment, as well as the changes in the relationship when looking at daily and person level averages. We also examined the instances of reported studying across the course of the assessment window between the intervention and assessment-only conditions. Finally, we explored the relationships between end of day and in the moment aggregated study time, with an additional focus on planned versus end of day reported study time for the intervention condition. In the literature review, we first present the discussion of academic motives and motivation in the context of self-regulation, methods used to measure self-regulation, and gathering self-regulatory data in the moment.

Self-Regulation

Self-regulation is one framework in which to investigate student engagement (Pintrich, 2000; Winne, 2001; Zimmerman, 2000). According to Zimmerman (1986), self-regulation consists of how someone is cognitively, behaviorally, and motivationally engaged in learning. This fits nicely into multidimensional conceptualizations of engagement, consisting of behavioral, cognitive, and affective components of engagement (e.g., Fredricks, Blumenfeld, & Paris, 2004) while an individual is directly in the moment with the academic task. As students self-regulate their learning during performance, they are performing on the task at hand (behavioral engagement), maintaining focus while controlling distractions (cognitive engagement), and persisting because of some degree of interest or perceived value (affective engagement). Zimmerman (2008) further refined the conceptual framework to include how students use their mental abilities to influence performance. Performance then in turn influences cognitions and motivation, thus creating a feedback loop (Hattie & Timperley, 2007). In this model, there is a cyclical nature among motivation, cognitive abilities, and strategies, which also aligns with Bandura's (1986a) notion of reciprocal determinism. Self-regulation has been related positively to academic outcomes such as study success, course performance, and overall academic performance (Chen, 2002; Hadwin et al., 2001; Heikkilä & Lonka, 2006; Kitsantas et al., 2008; Nota et al., 2004; Winne & Perry, 2000). Here we will discuss how different aspects of motivation and motives fit within the self-regulatory framework.

Forethought. Self-regulation consists of three phases that are interconnected. The first phase is the forethought phase, where students' prior beliefs and skills are used to prepare for engaging in a task. People engage in task analysis (goal setting and planning) to direct their behavior, as well as reviewing motivational beliefs (e.g., self-efficacy, outcome expectations, interest, goal orientations) which may direct the intensity and level of engagement in the task and are revisited throughout all stages of the self-regulation cycle (Schunk & Ertmer, 2000). When students set a goal, they consider what specific outcomes they plan to complete, and are more likely to commit to the goal when the goal is specific as well as realistic (Locke & Latham, 2002, 2006; Winne, 2011). After students review a goal, they create a plan for how to complete the specified goal considering numerous factors including: due dates, current knowledge, and task difficulty (Dunlosky & Hertzog, 1998; Son & Kornell, 2009).

Son and Kornell (2009) examined students planning intentions for studying and found that students will dedicate most study time to difficult tasks, while first completing easier tasks. There may be bias in study intentions such that students expect to study more in duration and across a longer period than actual time spent study. Blasiman et al. (2017) examined students planned intentions for studying versus a series of recalled reports of study sessions across the semester. They found students overestimated the time they planned to spend studying versus their retrospective reporting of how much time they studied. With both the planning and recall, researchers asked participants to report over a long period, i.e., two weeks for planning and seven days for the recall. Thus, both situations may have instances of bias in regard to the temporal distance from the behavior or planned behavior. To help with this, data regarding plans and study habits should be collected closer to the actual study sessions to limit potential temporal issues.

Additionally, during the forethought phase, students address prior motivational beliefs that may direct their persistence and intensity in the task. For example, there is evidence to suggest that higher self-efficacy is associated with setting specific goals that are attainable (Zimmerman et al., 1992; Zimmerman & Martinez-Pons, 1990). Students may use perceptions of self-efficacy to direct how much time and attention they need to use to complete their goals, even if perceptions of efficacy may not direct students to direct appropriate attention and resources towards studying (i.e., spending more time on studying but using ineffective methods; Zimmerman et al., 1992). Students may also engage or persist more in tasks they find meaningful to their future or in content they find interesting (Beymer et al., 2018; Durik & Harackiewicz, 2007; Harackiewicz et al., 2002; Hidi & Harackiewicz, 2000; Lee et al., 2014; Mitchell, 1993).

Performance. The second phase is the performance phase, where people exert self-control of engagement within a task while monitoring how they are performing.

First, they determine what strategies they need to use while engaging in the task. For example, while students are studying, they determine if a rehearsal strategy, such as reading over a textbook is sufficient for their purpose, or if they should use a deeper study strategy such as creating a concept map or summarizing material (Weinstein et al., 2000; Weinstein & Mayer, 1986). While there are associations with using higher level cognitive strategies and subsequent performance, there are also reports of overuse of ineffective strategies, suggesting students believe longer periods of using rehearsal strategies are more beneficial to learning (Morehead et al., 2016; Nota et al., 2004).

In the performance phase, students also may engage in metacognitive monitoring, which involves students determining if they need to make changes in study strategies and attention. They compare how and what they have accomplished, and whether the task has been adequately completed or if more time is needed. Winne (1995, 2001) describes metacognitive monitoring as a crucial feature of self-regulation because monitoring informs goal adherence, changes in planning, and self-judgments. When students exert changes based upon monitoring, they are using metacognitive control. These changes can happen multiple times, and within short time frames, during a single study session.

Self-Reflection. In the self-reflection stage, people further evaluate how they did on the task as well as reflect on why performance was successful or not. Students may have emotional responses to how well or poor a task went and attribute reasons for their successes or failures. These attributions may be adaptive or maladaptive (Weiner, 1986). For example, students may attribute their successes to effective strategy use, which would be viewed as an adaptive attribution. In contrast, students may attribute their lack of understanding to the material being too difficult or an instructor wasting the student's time, which are both maladaptive. This leads to greater insight and planning for the next instance of engaging in the behavior. With adaptive attributions, people are more likely to feel satisfied with their performance and associations with increased engagement. With maladaptive attributions, however, people are more likely to avoid or reduce further engagement to protect from negative feelings (e.g., procrastination, behavioral and cognitive disengagement; Zimmerman & Moylan, 2009).

Measuring Self-Regulation

One way to measure facets of self-regulation include single-instance survey and interview protocols. Some common examples of self-report measures include the Motivated Strategies for Learning Questionnaire (MSLQ; Pintrich et al., 1993), the Learning and Study Strategies Inventory (LASSI; Weinstein et al., 1987), and the Self-Regulated Learning Interview Scale (SRLIS; Zimmerman & Martinez-Pons, 1986, 1988, 1990). While these methods provide some insight into pieces of self-regulation, they do not capture the full complexities of the self-regulation process (Winne & Perry, 2000).

Instead of measuring self-regulation at a single timepoint, and thus considering self-regulation as a stable trait, there are a variety of methods to measure self-regulation as a context specific event (Cleary et al., 2012). Some of these methods include using think aloud protocols during a task (Ericsson, 2006), structured diaries completed during a task, or behavioral traces of participant movement during the task (Jamieson-Noel & Winne, 2003; Perry & Winne, 2006; Zhou & Winne, 2012). The similarities among these methods is that participants complete measures of self-regulation while immersed in a task. As of yet, no one method seems best suited for capturing all aspects of self-regulation. For example, researchers using a behavioral trace gain insight about how participants move through a task, but do not directly capture the full thought process of participants (Jamieson-Noel & Winne, 2003; Perry & Winne, 2006; Zhou & Winne, 2012).

One way to study self-regulation as a full process is through self-regulatory microanalysis, which is where participants engage in all three phases of self-regulation at the task level (Cleary et al., 2012). In this process, researchers gather behavioral, cognitive, and motivational variables of interest while participants are engaged in the task in a systematic way. Researchers interview participants with questions targeted towards specific steps of the self-regulation loop and monitor performance as participants engage in a specific task. This method has been used in several domains including athletics (Cleary & Zimmerman, 2001; Kitsantas & Zimmerman, 2002), nursing (Cleary & Sandars, 2011), and academics (DiBenedetto & Zimmerman, 2010; Follmer & Sperling, 2017; Zimmerman & Kitsantas, 1999). The goal is to capture students' thoughts and processes in the moment for various stages of the self-regulatory feedback loop. Students may be asked to set a specific goal and plans for how they will read the journal article (forethought), asked about perceived comprehension and perceptions of efficacy (performance), and attributions for what went well or not well during the task (self-reflections). Given the intensive nature of these tasks, they are usually with smaller samples of participants. Furthermore, some of the aforementioned tasks have been completed in a laboratory setting, and participants may not have used the same self-regulatory processes as they would in everyday life.

There have been some advances in studying aspects of self-regulation in everyday life using in the moment data collection, which tend to be referred to as ecological momentary assessment (EMA; Shiffman et al., 2008) or experience sampling methodology (ESM; Csikszentmihalyi et al., 1977). When compared to in-lab protocols (e.g. Follmer & Sperling, 2017), these methodologies allow for studying the variables of interest in a variety of contexts. For example, Ketonen et al. (2018) examined perceived motivation behind studying and associated academic emotions throughout the day across a 14-day period. Based upon their findings, motivation behind goal setting was associated with academic emotions throughout the day; however, by having students write goals, they were intervening in student behavior. Additionally, Xie et al. (2019) examined relationships among self-regulation and study related behaviors using event-based (where participants responded when they were studying) or interval-based (prompts sent at predetermined times to participants). While Xie et al. examined different prompt types to capture students' study habits, they did not examine the prompts concurrently. With their reports of event-based prompting, they reported no missing data which is unlikely given their response rates in the signal-contingent and event-based studies (both approximately 68 percent in both studies). This makes an assumption that while participants only responded approximately 68% of the time in the event-based study, that no study sessions were missing. They had participants plan out all study events prior to the implementation of the protocol while in the current study, we gave participants the ability to initiate their own study events while in the study. In the current study we utilized a two-group design, including an intervention condition (similar to Ketonen et al., 2018) and an assessment-only condition, to examine differences in reported studying behavior, motivation and academic emotions.

The Present Study

The purpose of this study was to explore group differences (intervention vs. assessment only) regarding the implementation of a self-regulatory intervention. Specifically, we were first interested in group differences in academic study time, by having participants in the intervention condition specify academic goals for daily study time and for each course as well as set specific goals at the beginning of each study session. The assessment-only condition had the option to report if they set a goal, but only for the study session. We were also interested in the relationships among academic motivation and motives across the course of the study. We monitored students' study time, academic motivation and motives, along with their testing and assignment schedule across 14 consecutive days. These data are nested hierarchically where specific situations are nested within specific days within specific participants. This allowed us to examine the individual fluctuation for each individual across situation to situation, as well as patterns between intervention and assessment-only students across the 14-day period. Specifically, we were interested in addressing the following questions (below) along with the overarching question of whether there were group differences between the intervention vs. assessment-only conditions for each question:

Q4 Are there differences in reported daily study time between conditions?

Q4a For the intervention condition, are there differences in planned versus reported end of day study times?

Q5 Are there patterns in the relationship among academic motivation and positive and negative emotions when examined over time?

Q6 Does academic motivation and emotions relate to reports of study engagement?

Methods

Participants and Procedures

Participants included 49 undergraduate students (63.3% female, average age = 20.20 years, *SD* = 3.79 years) enrolled at a public comprehensive university in the western United States (acceptance rate 90%). The participants were majority freshmen (63.3%) and Caucasian (79.6%; 18.4% identified as Caucasian including Latino). There were a diverse set of majors in the sample including: Psychology (*n* = 10), Sports and Exercise Science (*n* = 6) and Business (*n* = 5) with various other majors. Approximately one quarter of participants in the sample (*n* = 13) met the criteria for academic probation (cumulative GPA less than 2.0). In our sample, the average cumulative GPA was 2.71 (*SD* = 1.03). For eligibility, students had to be: over 18 years old, enrolled as an undergraduate student at the university of interest, and have a smartphone capable of downloading the application used in the study.

Participants were recruited through the psychology department research pool, as well as email announcements sent to faculty with a request to post to online learning management systems. Participants were assigned to an assessment-only or intervention condition, and they completed a baseline appointment prior to the mobile assessment. Data collection for the study used the mobile application “RealLife Exp” from Lifedata, which is an EMA application based on participants own smartphones (lifedatacorp.com). Participants were trained in the baseline appointment on how to use the application, including where to start user-initiated session.

Participants were prompted three times a day during the 14-day study window, and they had up to one hour to respond to the signal-contingent prompts sent by the researchers (Researcher Generated Prompts; RGPs). There was a random signal-contingent schedule within three defined blocks (8:00-12:20; 12:30-4:50, and 5:00-10:00), with one reminder sent thirty-minutes after the initial signal (see Hektner et al., 2007). Participants had up to one-hour to complete the prompts. Participants were instructed to complete the prompts as soon as they received them. In addition to the abovementioned prompting schedule, participants were asked to initiate an event-related session in the app (user-initiated) whenever they engaged in studying (as defined as engaging in class preparation, reading, etc., that does not result in a direct grade). Participants received follow-up yoked-RGPs thirty-minutes after initiating study sessions.

In this study, there was a possibility of 42 signal-contingent RGPs delivered to all participants, or 2,058 questionnaires overall (42 questionnaires per person for 49 participants, with a 65.40% overall response rate). The overall response rates did not differ by intervention and control conditions, t (47) = 0.35, p = .73. Additionally, participants received follow-up yoked-RGPs dependent upon the number of completed user-initiated sessions (Range 0-14 sessions; median = 4; mode = 3).

Data Sources

Baseline measures. Along with collecting demographic factors (age, gender, major, status in school, transfer status, cumulative GPA (cumGPA), and hours spent working per week), we also descriptively gathered data about participants' typical study habits using a measure compiled by Morehead et al. (2016), which contained 13 questions to capture different aspects of how participants study. We use this measure to describe the sample in terms of their baseline study habits. We also collected various self-regulatory and emotion variables to use as covariates in our analyses. We measured metacognitive self-regulation using the Motivated Strategies for Learning Questionnaire (MSLQ; Pintrich et al., 1993). Participants rated 13 items on a 1 (*Not at all true of me*) to 7 (*Very true of me*) rating scale. Finally, we addressed baseline study related anxiety with a subscale from the Achievement Emotions Questionnaire (AEQ; Pekrun et al., 2011). The Cronbach's alphas for the scales are as follows: MSLQ Self-Regulation (α = .71), and AEQ Anxiety (α = .90).

Ecological Momentary Assessment/Ecological Momentary Intervention prompting.

Signal-contingent researcher generated prompts (RGPs). All participants received these prompts three times a day for the 14-day assessment period. Regardless of condition, participants were asked about the main activity they were doing when prompted. Next, participants were asked whether they had studied since the last time prompted (both in a *yes/no* and an *amount of time* format). Additionally, participants were asked to rate their academic motivation ("How motivated are you to engage in academics right now") on an 11-point rating scale from 0 (not at all) to 10 (highly motivated). Finally, participants were asked to rate seven academic emotions at that moment using a modified version of the Positive and Negative Affect Schedule (PANAS; See Ketonen et al., 2018) on a scale from 1(not at all) to 7 (very much). We used the following indicators (Interest, Determined, and Anxiety) from the PANAS. We also created an additional indicator for Boredom. For the last prompt of the day, participants were asked about how much overall time they spent studying for the day as well as class attendance (i.e., whether they missed class, if so, how many and which classes).

Ecological Momentary Intervention interval researcher generated prompts. For the intervention condition, participants were asked during the first prompt of the day to set a goal for how much time they were planning on studying for the day, and to specify for which classes they planned on studying. During the last prompt of the day, they were asked to set a goal for the next day studying.

Data Analyses

There were 13 participants who responded to less than 50% of the signal-contingent RGP prompts. We compared baseline cumGPA, as well as academic motivation and emotion variables to see if there were any systematic differences between those who did or did not respond over 50% of the time. No differences were found between these factors, so the 13 low-responding participants were removed from subsequent analyses due to the number of missing data and potential bias. Out of those 13 participants, 7 were in the assessment-only condition. This resulted in 18 participants from each the assessment-only and intervention conditions included in the analyses.

The data are organized hierarchically where situations (Level 1: n = 1512) are nested within days of the study (Level 2: 14 days; n = 504 instances) and the days are nested within participants (Level 3: n = 36). For some questions, we did not consider changes over time and were interested in the group level differences. In these instances, we used baseline data as well as aggregated EMA data for analyses.

Daily reported study time. To address Q4, we used end of day reported study time as the outcome to examine potential group differences while accounting for participant cumGPA, and MSLQ self-regulation. For Q4a, we examined the relationship between planned vs reported end of day study time, while controlling for participant cumGPA, MSLQ self-regulation, within only the intervention condition since the assessment-only control group did not complete the prompts for planned study time.

Relationship of emotions to academic motivation and engagement. To address Q5 (outcome academic motivation) and Q6 (engagement in studying), a series of linear and generalized mixed models were fit using R packages “lme4” and “lmerTest” for approximate p-values (Bates et al., 2014; Kuznetsova et al., 2017). For Q5, a linear mixed model was fit using academic motivation as the outcome, with time point specific positive emotions (Interest, Determined) and negative emotions (Anxiety, Boredom), as well as condition (intervention vs. assessment-only).We looked at the relationships for academic motivation at the same moment with emotions, as well as the subsequent moment (time-lagged). For Q6, we used reports of participants’ responses of studying at the same time point as when they responded to academic motivation and emotions. With this in mind, studying reports were defined as time since the last prompt (i.e., engaging in studying across the prior timepoint) as the outcome of interest while using academic motivation and emotions as predictor variables. Each EMA variable used in these models were time-dependent covariates, so we created a person level average and deviations from the person level average to examine the relationships across time. Due to the longitudinal nature of the data, we included an additional random term to account for repeated observations. We accounted for cumGPA, weekday vs. weekend, and condition (intervention vs. assessment only).

Results

Descriptive Statistics for Study Behaviors

Prior to addressing the research questions, it is important to address participants' baseline reports of study strategies and time allocation. Approximately half of participants (n = 25) report they study whatever is due next or overdue, while only six participants reported planning out their study time. The majority of participants (n = 33) report rereading sections of material as part of their regular study strategy. Additionally, the majority of participants (n = 29) noted that they space out their studying instead of cramming before a test. When asked in a separate question about their regularly endorsed strategies though, 31 participants reported the use of cramming. Finally, only 12 participants did not view a difference between engaging in studying and doing homework.

Research Question Four

Q4 Are there differences in reported daily study time between conditions?

Q4a For the intervention condition, are there differences in planned versus reported end of day study times?

On average, participants reported spending 17.57 (*SD* = 40.93) minutes studying since the last prompt with a range of 300 minutes (Range 0-300 minutes) and median of zero. With regard to the end of the day prompting, participants reported a daily average of 41.48 (*SD* = 74.12) minutes studying (Range 0-600 minutes) with a median of zero. When looking at weekly averages, participants in the assessment only condition reported an average of 190 minutes studying (*SD* = 199.56) compared to the intervention condition

(*M* = 261, *SD* = 391.74), which were not statistically significant, t (34) = -0.69, p = .49. For the second week, the averages were reversed with participants in the assessment-only condition reporting an average of 313.65 minutes studying (*SD* = 295.31) compared to the intervention condition (*M* = 193.06, *SD* = 215.44), which again were not statistically significant, t (33) = 1.39, p = .18.

To look at group differences in reported end of day study time (Q4), we used end of day reported study time as the outcome while accounting for participant cumGPA, and MSLQ self-regulation. The majority of responses for both end of day reports as well as during the day were zero. There was a possibility of 504 occurrences, of those there were 408 completed responses (Response rate = 80.95%) across the participants. The average report of daily time spent studying was 41.48 minutes (*SD* = 74.12 minutes) while the trimmed mean was 24.74 minutes. This trimmed mean removed the lowest and highest ten percent of responses, which were extreme scores and gives a better representation of the majority of reported study times. The median response was zero, which suggests a large percentage of responses were zero minutes. We first looked at the correlation between end of day report versus EMA summed reports for time spent studying within the same day (the 3 time points across each day) using a linear mixed model accounting for day in study and a random term for participant. We did not find group differences with end of day reported studying. We did find a moderate relationship between time studied variables (B = .46, p <.05), suggesting that reports through the day were positively related to the end of day report across both conditions. We next accounted for cumGPA, MSLQ self-regulation, and condition. In this model, self-regulation was positively associated with end of day reports of studying (B = 2.15, p < .05).

For the intervention condition, we examined planned goal time for studying, which was part of the intervention, and end of day reports of time spent studying (Q4a). There was a positive association between planned at the beginning of the day vs end of day reported time (B = 0.52, $p < .05$). Additionally, baseline levels of MSLQ self-regulation were positively associated with end of day study time (B = 2.16, $p < .05$). When looking at the distribution of responses, it appears that there was a wider variety of planned studying compared to the end of the day reported study time (see Figure 3 for planned versus end of day reports for the intervention condition).

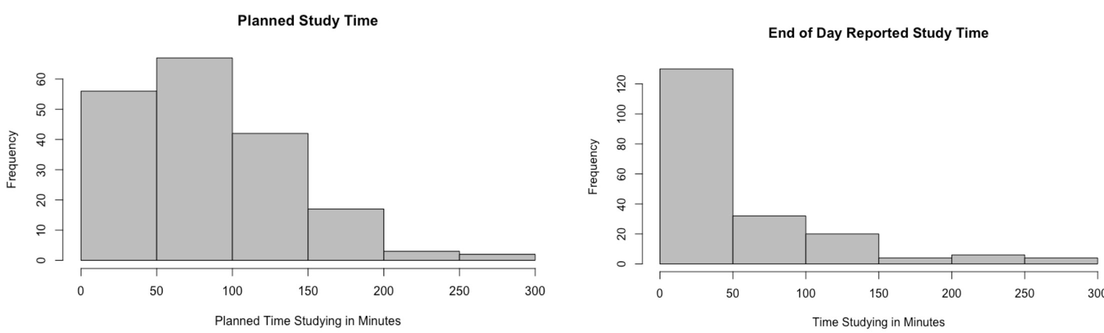

Figure 3. Planned and end of day reported time spent studying for the intervention condition.

Research Question Five

Q5 Are there patterns in the relationship among academic motivation and positive and negative emotions when examined over time?

Descriptive statistics for the aggregate EMA variables by condition are presented in Table 4. Additionally, we present bivariate correlations for levels 1 (situation level), 2 (day in study average) and 3 (participant level) among academic motivation and emotions in Table 5. Based upon the correlations, we can see that person level averages typically show higher relationships among variables compared to momentary instances, which shows the variability in participants' responses over the 2-week period in the study.

Table 4

Aggregate Descriptive Statistics of Ecological Momentary Assessment Related Variables

	Assessment Only ***M* (SD)**	Intervention ***M* (SD)**	Overall ***M* (SD)**
Time Study Avg	43.18 (35.13)	40.88 (48.14)	42.03 (41.55)
Week One Study Avg	190.00 (199.56)	261.00 (391.74)	225.50 (308.51)
Week Two Study Avg	313.65 (295.31)	193.06 (215.44)	251.63 (260.74)
Academic Motivation	4.11 (1.64)	4.08 (2.47)	4.10 (2.06)
Interest	3.70 (0.91)	3.58 (1.39)	3.64 (1.16)
Determined	3.99 (0.99)	3.69 (1.50)	3.84 (1.23)
Anxious	2.87 (1.31)	2.99 (1.50)	2.93 (1.40)
Bored	3.06 (1.36)	2.75 (2.75)	2.91 (1.27)
MSLQ-SR	46.92 (7.79)	45.21 (8.02)	46.08 (7.87)
AEQ_ANX	31.32 (10.14)	33.67 (8.76)	32.47 (9.47)

Note: Time Study variables were computed based upon averages of end of day reports for participants (i.e., average of 14 time points for 36 participants as well as based upon condition). Motivation and emotions were the average of 42 time points for 36 participants overall as well as based upon condition.

Table 5

Bivariate Correlations of Ecological Momentary Assessment Academic Motivation and Emotions

Variables	Bivariate cross-sectional correlations						
	1.	2.	3.	4.	5.	6.	7.
	L3: Person Level						
1. Motivation	1						
2. Interest	.77**	1					
3. Determined	.78**	.89**	1				
4. Anxious	.19	.16	.26	1			
5. Stress	.11	.09	.21	.94**	1		
6. Irritable	.11	-.09	.01	.60**	.66**	1	
7. Bored	-.22	-.44**	-.30	.14	.16	.61**	1
	L2: Day in Study Level						
1. Motivation	1						
2. Interest	.78**	1					
3. Determined	.75**	.85**	1				
4. Anxious	.23**	.18**	.25**	1			
5. Stress	.18**	.12	.21**	.87**	1		
6. Irritable	.16**	-.02	.05	.54**	.59**	1	
7. Bored	-.14*	-.31**	-.22**	.14*	.13*	.49**	1
	L1: Situation Level						
1. Motivation	1						
2. Interest	.74**	1					
3. Determined	.73**	.81**	1				
4. Anxious	.20**	.17**	.24**	1			
5. Stress	.15**	.13**	.20**	.77**	1		
6. Irritable	.13**	.02	.07	.49**	.53**	1	
7. Bored	-.12**	-.23**	.14**	.17**	.16**	.42**	1

Note: $^{**}p<.01$. $^{*}p<.05$.

We fit two models with academic motivation as the outcome, one examining the association between academic emotions and motivation within the same moment (same-moment model) and a second model examining the association of academic emotions with motivation at the subsequent time point (time-lagged model). The models were identical except for the outcome of academic motivation at the next instance for the second model. First, there was a marginal intervention difference, where on average the intervention condition had higher academic motivation than the control group (B = 0.97,

p <. 05). Additionally, in the same-moment model, average EMA interest was positively associated with academic motivation (B = 1.59, $p < .001$), while changes in interest over time was negatively associated with academic motivation (B = -1.19, $p < .001$), such that those who had higher momentary interest had lower academic motivation and vice versa. A negative association across time was also found for EMA anxiety and academic motivation (B = -0.17, $p < .001$), such that those with higher momentary anxiety had lower motivation and vice versa. With regards to the time-lagged model, there were similar relationships as described above for EMA interest and anxiety, but no intervention differences (see Table 6 for parameter estimates for same-moment and time-lagged models).

Research Question Six

Q6 Does academic motivation and emotions relate to reports of study engagement?

We fit two models with study engagement as the outcome, one using negative emotional states (i.e., anxiety and boredom) and the other using positive emotional states (i.e., interest and determined). Each EMA variable used in these models were time-dependent covariates, so we created a person level average and deviations from the person level average to examine the relationships across time. We used the same control variables in all models (cumGPA, weekday vs. weekend, and condition). Parameter estimates are presented in Table 7. We adjusted the number of emotions used within each model to account for convergence issues, which led to the removal of interest or determined in the positive model. Additionally, due to convergence issues, we had to use reports of engagement in the same moment (which reflected presence of studying since the last prompt). In both models, there was a lower probability of reporting studying on the weekend compared to the weekday, and the probability to report studying went down over the two-week timeframe. In the positive emotion model, participant average academic motivation was positively associated with reporting studying (B= 0.44, OR = 1.57, $p < .05$) but their changes from their average motivation across time was associated with a lower likelihood to report studying (B= -0.14, OR= 0.87, $p < .05$), such that those with higher motivation than their average over the two week period had a lower likelihood of reporting prior studying and vice versa. In the negative emotion model, participants' change in anxiety across time was associated with a lower probability to report studying (B= -0.13, OR = 0.87, $p < .05$), such that those with lower momentary anxiety were more likely to report prior studying and vice versa.

Table 6

Parameter Estimates of Academic Emotions and Motivation

	Same-Moment Model			Time-Lagged Model		
	B (SE)	*t* (df)	*p*	**B (SE)**	*t* (df)	*p*
Intercept	-4.34 (1.38)			-4.33 (1.53)		
Condition (Intervention)	**0.97 (0.46)**	**2.08 (26.70)**	**.05**	0.81 (0.51)	1.58 (27.23)	.13
Average EMA Interest	**1.59 (0.21)**	**7.54 (26.57)**	**< .01**	**1.65 (0.23)**	**7.14 (27.01)**	**<.01**
Interest over time	**-1.19 (0.04)**	**-31.89 (1067.94)**	**< .01**	**-0.35 (0.06)**	**-5.99 (865.26)**	**< .01**
Average EMA Boredom	0.33 (0.20)	1.67 (26.56)	.11	0.39 (0.22)	1.74 (27.38)	.09
Boredom over time	-0.01 (0.04)	-0.24 (1039.69)	.81	0.07 (0.07)	1.06 (866.79)	.29
Average EMA Anxiety	0.03 (0.16)	0.18 (26.11)	.86	-0.10 (0.17)	-0.60 (27.00)	.55
Anxiety over time	**-0.17 (0.04)**	**-3.80 (992.46)**	**< .01**	**-0.15 (0.07)**	**-2.09 (865.01)**	**.04**
Time in study	0.00 (0.01)	0.37 (33.20)	.71	-0.01 (0.01)	-1.07 (869.78)	.29
Cumulative GPA	**0.45 (0.20)**	**2.24 (26.79)**	**.03**	**0.54 (0.22)**	**2.44 (28.02)**	**.02**
Weekend vs. Weekday	**-0.26 (0.12)**	**-2.21 (1061.96)**	**.03**	-0.31 (0.19)	-1.65 (869.54)	.10

Table 7

Parameter Estimates of Studying across Prior Interval

	Model 1: Studied Positive			Model 2: Studied Negative		
	B (SE)	OR	*p*	**B (SE)**	OR	*p*
Intercept	-3.33 (1.35)			-0.66 (1.55)		
Cumulative GPA	0.41 (0.34)	1.51	.23	0.52 (0.37)	1.69	.16
Condition (Intervention)	0.55 (0.75)	1.74	.46	0.46 (0.82)	1.58	.58
Weekday vs. Weekend	**-0.56 (0.21)**	0.57	.01	**-0.70 (0.21)**	.50	< .01
Session Time	**-0.02 (0.01)**	0.98	.01	**-0.02 (0.01)**	0.98	< .01
Average Academic Motivation	**0.44 (0.18)**	1.57	.01			
Motivation Deviation	**-0.14 (0.03)**	0.87	<.01			
Average Anxiety				-0.34 (0.29)	0.71	.23
Anxiety Deviation				**-0.13 (0.07)**	0.87	.04
Average Boredom				-0.01 (0.32)	0.99	.97
Boredom Deviation				-0.09 (0.07)	0.92	.19

Discussion

In the present study, we examined intervention versus assessment-only comparisons within the relationships among academic motivation and emotions across time. We additionally examined associations among situation level academic motivation and emotions with academic engagement (endorsing studying). Finally, we examined associations with reported end of day study time, and consistency in reporting for the intervention condition between planned versus reported study time.

To begin, it is of importance to explain the context of the study. The majority of the sample participated within the last two-weeks of the academic semester. This contextualization is important with regards to interpreting most findings in this study. We did not find group differences between the intervention and assessment-only conditions for most of the outcome variables we examined.

Specifically, we did not see differences between the conditions for reported end of day studying (Q4), as well as endorsing studying since the last prompt (Q6). Descriptively, we had large variability in the amount of time participants reported studying, but the weekly averages were approximately four hours per week studying. The wide variability in participant study times suggests that participants were not spacing their time studying, which is interesting given many of the participants endorsed spacing their studying as a strategy during the baseline appointment. There is also evidence to suggest students on average may have spent lesser amounts of time toward studying compared with previous research. In our sample, the majority of the participants were taking between 12 and 15 credits (full-time) in the semester while reporting 4 hours on average of studying. This is compared to previous research that has investigated the time college students spend studying and tends to be higher than 10 hours or more depending on the study (Babcock & Marks, 2011; Hanson, Drumheller, Mallard, McKee, & Schlegel, 2010). For example, Hanson et al. (2010) reported participants spending approximately the same amount of time going to class compared to studying for those courses.

Additionally, we did see some marginal differences between the two conditions on academic motivation within the same moment model (Q5). One possible reason for the lack of differences when looking at next time-point motivation was the controlling nature of prompting participants to set daily time goals. In Ketonen et al. (2018), participants were asked to set daily goals, but then they were asked about the perceived autonomous/controlled nature of the goals. They found that perceptions of autonomous motivation were associated with positive emotions through the day. We limited the number of questions we asked participant to minimize burden and did not ask about the autonomous nature of their motivation.

When looking at end of day reports of studying and in the moment reports of studying (Q4 and Q4a), there was a moderate relationship. This relationship may be attenuated for a number of reasons. The first is missing data. With the way daily totals were calculated, if a participant did not respond at any given time point, any missing time was not accounted for in calculating a daily total. The second reason is rounding of data. Participants may over or underreport their time spent studying based upon memory bias from the day (Stone & Shiffman, 2002). This is one reason why we should be cautious with using reports of how much time students' study by their reports over large periods of time, e.g., days or weeks. When even looking at the end of day reports of study time, participants reported as high as 600 minutes spent studying. There was also a moderate relationship found between planned versus end of day reported studying for the intervention group with the same caveats as mentioned previously, which draws into focus the need for interventions to impact the full self-regulation cycle across all phases. For the end of day reports of studying, there were missing or no reports of studying in approximately half of the cases, which can bias the association. Based upon the findings of Ketonen et al. (2018), it would have been beneficial for participants to report motivation for their time-based goals, but this was not addressed in this study.

Regardless of condition, we found similar findings regarding associations with academic motivation (Q5) and endorsement of studying (Q6) for relationships with academic motives, as well as factors such as weekday vs. weekend. In both models, we found that participants were likely to have lower academic motivation on the weekend, as well as a lower likelihood of endorsing studying. Particularly, we found that the odds of not reporting studying over the weekend were approximately 2:1 This is also in line with more recent reports of declining amounts of time spent studying in general (Babcock & Marks, 2011; Nonis & Hudson, 2006). We also found that average academic motivation was positively associated with the likelihood of reporting studying, and a negative relationship of the change of motivation and anxiety across time was associated with a probability of not reporting studying. Thus, as participants' motivation fluctuates higher from their average over time, they had a lower probability of reporting studying. These associations may need to be observed in recursive models, where we examine both directions of the motivation-engagement relationship, because prior studying may enhance participants perceptions of academic motivation with a potential sense of accomplishment. We also acknowledge a limitation when examining these data in a binary manner. We addressed studying in two different ways during the signal contingent researcher-generated EMA prompts: as an endorsement of behavior since the last prompt (yes/no), and in the amount of time since last prompt (scrollbar in minutes). We found a large number of inconsistencies in reporting for those who stated they did not study and then reported an amount of time studying since last prompted and vice versa (see Chapter 4 manuscript). Since the behavioral endorsement question came first in the protocol, we viewed it as the indicator of engagement in studying. However, the opposite is possible in that participants might have responded too quickly to this question and the amount of time could be a better indicator of study engagement. One reason for this inconsistency may be a function of the question in the application itself. The question was automatically set to zero, and that zero response could have been from participants responding quickly as well to the amount of time question. Thus, this was a limitation for this study that needs to be taken into consideration when drawing conclusions and followed up with further research investigating how EMA protocols are designed and potential constraints of technology used for these approaches.

With regards to the academic emotions for both sets of models, we found that fluctuations in EMA reported anxiety were negatively associated with both academic motivation, as well as the likelihood of reporting studying. For academic anxiety, it could be expected that greater fluctuations might relate negatively to academic motivation and engagement (Dunn, 2014; Legault, Green-Demers, & Pelletier, 2006; Pekrun, Goetz, Titz, & Perry, 2002). Individuals who have higher momentary instances of anxiety, when compared to their overall average (or baseline/general anxiety level), could view lower motivation as a coping mechanism (Arthur, 1998). With regards to motivation, we also saw that fluctuations in EMA reported interest were negatively associated with motivation. Students' interest in academic outcomes and course content may be fluctuating more towards the end of the semester, but they may still feel motivated to persist as a means to finish the semester. Thus, there might be more variation in academic interest, but they are still motivated to finish out the semester. These patterns would be worth following up in future studies across the semester, as there could be different motives associated with students' academic motivation depending on the period of time within the semester.

Limitations

The first limitation stems from a lack of reporting of the behavior of studying during the 14-day period of the study, which may have not been long enough to capture study patterns. This could be from an absence of the behavior, or an underreporting of the behavior. For the latter, participants were instructed to focus their report of studying to one course at a time, even when studying for multiple courses. This was done to provide anchoring for participant responses but could have led to underreporting of study instances. We also asked participants not to view studying as preparing a product to turn in for a grade. In some courses, this may have limited reports of studying (e.g., courses where practice problems could be viewed as both studying and preparing a product). This is plausible given that the majority of participants at the baseline session viewed a difference between studying and completing schoolwork, which could have led to fewer instances of reported studying. Across all retained participants, for the responses to the signal-contingent RGPs there were 386 instances of reported study instances compared to

777 where they reported not studying. This imbalance may have led to certain associations being found with lower studying across the study. This is an interesting finding given that the majority of these instances were gathered during the second half of the semester for this study, with approximately 25 percent occurring in the two weeks leading up to finals week. One possible reason for the lack of studying may be perceptions of not needing to study (Krohn & O'Connor, 2005). The lack of studying may be also associated with not having a major assessment in the course besides the final, which could be associated with procrastination to study during the final few weeks and we did not account for measuring aspects of study procrastination. We stopped data collection for participants the last day of the regular semester, which did not account for finals week. Thus, we may have missed a window of studying as students progressed to finals week, but this pattern of studying would not be considered regular studying. Students may be preparing for multiple examinations within a short window, which may or may not be cumulative in nature. While we do have some evidence about baseline levels of self-regulation associated with their reported study patterns, we acknowledge that other variables may have accounted for the amount of reported studying (e.g., in the moment measures of procrastination; Wieland et al., 2018).

Another limitation involves the characteristics of the sample. Approximately 25 percent of the sample met the criteria for academic probation, where aspects of studying and regulation of learning would have in practice been beneficial. With these sample characteristics in mind, the length of study and intervention may not have been long enough to impact change in study behaviors and strategies. We additionally had student-athletes in the study, but they were not able to use electronic devices during their mandated study times, leading to possible lower responses. The information entered by student athletes in the app may be of use for tracking of athletes' study time and motivation towards study. With the software used in the current study, participants did not have to be connected to mobile data to receive prompts; only to upload responses from their phone to the server, which may alleviate the concerns of using technology during mandated study times.

Future Directions

The next step in this progression is to incorporate perceptions of autonomous and controlled motivation across self-regulation conditions regarding their goal-setting. This was an initial criticism of Ketonen et al. (2018) because they asked participants to report their daily goals. Within an assessment-only condition, participants may be asked if they have a goal for the day versus having them set a goal for the day, monitor their perceptions of autonomous versus controlled motivation within those moments, and the relationship to their reports of studying. To test the efficacy and effectiveness of the proposed intervention, it would be of benefit to test in samples of entering college students enrolled in first year experience courses compared to those that are not, as well as within specific majors (e.g., STEM fields).

Another possible direction involves influencing whether prompts are perceived to come from a course instructor rather than a researcher. Participants may respond to and engage with the intervention materials in a more consistent manner if they perceive the prompts are coming from a figure more associated with their learning.

Conclusion

The purpose of this investigation was to examine the implementation of an ecological momentary intervention using facets of self-regulation while collecting a number of ecological momentary assessments over a two-week period toward the end of an academic semester. We did see some marginal differences in academic motivation within the same moment between conditions, but no other differences were found regarding time spent studying across the course of data collection between conditions. It might be important to consider that intervening for academic self-regulation might need to happen at the beginning of a semester before study patterns are established or a more intense intervention might be needed at this point in the semester (e.g., providing information via signal-contingent prompting regarding spacing study time, using appropriate study strategies). It is also possible that this type of intervention may not be effective at changing study behaviors.

Based upon the findings, there were several methodological considerations that can be used in future research to see if differences in quality and quantity of study are present (i.e., further incorporation of reminders, time between prompting, and data collection windows). These aforementioned changes should be explored in subpopulations who report more engagement in study (e.g., STEM discipline majors, and those who complete mandated study times). While intervening, it may be of benefit to use the ever-changing affordances of technology to determine when to intervene in behavior (e.g., with larger fluctuations in factors such as academic motivation and emotional thoughts towards academics) and align with adaptive principles similar to JITAIs (Nahum-Shani et al., 2017).

CHAPTER VI

DISCUSSION

The purpose of this dissertation was to examine the feasibility and implementation of a self-regulation based ecological momentary intervention and be able to compare it with an assessment-only condition while utilizing ecological momentary assessment data. I presented the findings related to this work in the preceding manuscript chapters (IV & V). In the following sections, I first present and discuss the findings of Q7 (Number of study sessions), which was not included in either manuscript. I also discuss findings regarding the baseline microanalytic protocol and reasons for exclusion in the manuscript chapters. I next discuss the results of both manuscripts and connect how the results surrounding feasibility influenced decisions for the content-based analyses. I also discuss the limitations related to the study implementation and subsequent interpretations. Finally, I discuss directions for future research.

Number of Study Sessions

As a reminder, Q7 involved examining differences across condition in the number of completed user-initiated event-related study sessions, as well as yoked follow-up signal-contingent prompts. Before discussing the data, it is worth noting that there are limited studies that leverage user-initiated event-related responses and particularly a dearth in the educational literature. When looking at the scope of both manuscripts, this question did not appear to fit within the purview of either manuscript and thus is discussed here in the final chapter.

For the question of user-initiated events for studying, I first aggregated the total number of participant user-initiated sessions (not considering those initiated within five minutes of each other) as well as total number of completed follow-up sessions for analyses. I examined group differences in counts (i.e., total number of user-initiated sessions as well as completed follow-up sessions) while controlling for cumGPA, MSLQ self-regulation, BCS (self-control), baseline reports of study strategies (spacing-out versus cramming), EMA aggregates of the following variables for *total time spent studying*, *study-related academic anxiety* and *average academic motivation*. I did not see group differences for neither the user-initiated nor follow-up yoke-RGP models for the counts. For the user-initiated model, total time spent studying was associated with an increase in the count of user-initiated sessions (B = 0.03, $e^B = 1.03$, $p < .05$), which would make sense if they were initiating when studying more. Additionally, baseline reports of cramming (B = -.84, $e^B = 0.43$, $p < .05$), self-regulation (B = -.05, $e^B = 0.95$, $p < .05$), and average EMA academic anxiety (B = -.29, $e^B = 0.75$, $p < .05$) were all associated with a lower count of user-initiated sessions. For the follow-up yoked-RGP model, there were five instances of missing data for participants in the intervention condition where they did not receive follow-up prompts due to a programming error where prompt triggers were not set to deliver. I examined both entering zero for number of responses, as well as treating these data as missing. The model interpretations did not change, so these five cases were removed. In the model, only baseline reports of cramming were negatively associated with the count of completed follow-up yoked-RGP sessions (B= -1.31, e^B = 0.27, $p < .05$).

I did not find differences across conditions in terms of number of user-initiated event-based study sessions and subsequent yoked follow-up sessions. In one way, this shows a lack of adherence to research protocol (i.e., participants in the intervention condition were instructed to set a daily goal for studying, which in practice should have led to an initiated study session). Regardless of condition, I found that there was a negative relationship between average perceptions of academic anxiety and the count of user-initiated event-related sessions, which is in the expected direction. I also found a negative relationship between baseline self-regulation and the count of user-initiated event-related sessions, which may be explained by the notion that participants may understand when they need to study, and study more efficiently. On the other hand, participants may not be studying more efficiently, but instead cramming. This idea is plausible given the negative relationship of participant reports of cramming at baseline with number of event-related study sessions. In the current sample, we did find lower levels of self-regulation with baseline reports for regularly cramming versus those that space out their studying, $t\ (34) = -\ 3.23$, $p < .05$. With regards to the yoked follow-up sessions, which as a reminder, happened thirty minutes after the user-initiated sessions, there were five participants who responded to all follow-up prompts as instructed. For the rest of the participants, one possible explanation for missing prompts was that participants remained focused on their study session, but others could be that they had finished studying and switched their focus to other tasks, were focused on other tasks not involving their phone during the study session, or by distractors on their phone (e.g., social media; David, Kim, Brickman, Ran, & Curtis, 2015). I only found baseline reports of cramming to be negatively associated with a lower number of completed yoked follow-up prompts, where participants do not respond perhaps due to their focus preparing for an upcoming exam.

Microanalytic Protocol

Additionally, I did not incorporate aspects of the microanalytic protocol into the content paper (Chapter V). This decision was made for a number of reasons. First as previously mentioned, there was a lack of user-initiated study sessions during the 14-day monitoring period. The original intent of using the microanalytic protocol was to employ facets as controls for the EMA study events. Second, there were issues with getting participants to vocalize thoughts while reading the associated passage, which was a central aspect for providing data for this protocol. While participants were instructed to vocalize any thoughts or actions while reading the passage, the majority of participants sat in silence while reading. This may have been partly because of the content of the passage (Mythology) and participants were focused on the upcoming assessment that they were told would take place on the passage. During pilot testing, I tried a couple of strategies to help facilitate participant vocalizations including modeling a response using the practice passage they read prior to the task. When this did not work to get participant responses, I turned my focus to a behavioral checklist for what behaviors participants engaged in while reading the passage.

Furthermore, I initially thought it would be of benefit to try a passage and assessment that was not tied to a content area in which participants were likely to have prior knowledge. This was a thought to capture self-regulation for reading over using content knowledge to facilitate their understanding of the passage. In future work, I will incorporate a different assessment measuring knowledge for a topic, not just comprehension of material. For example, Follmer and Sperling (2017) used a measure of statistics when carrying out their microanalytic protocol. In future work, it would be of benefit to try different measures for a microanalytic protocol. With this in mind, though, there may be further issues with standardization of assessment scores.

With regards to the data captured from the microanalytic protocol, I asked participants a measure of perceived efficacy for mythology prior to reading the passage. Participants on average reported an efficacy of 42.02 out of a possible 100 (SD = 23.17; range = 0-90). After reading the passage, participants on average reported an efficacy of 77.90 (SD = 15.52; range = 30-100), which was significantly higher than pre measures of efficacy, t (48) = 10.25, $p < .05$. I additionally asked participants about how many questions they believed they answered correctly on the reading assessment (out of 8 possible correct). The most common response was 5 (34.7%), followed by 6 (28.6%) and 4 (12.2%). While these data are interesting regarding student thought and motivation processes while in the microanalytic task, they were not as interesting to present on their own without EMA data as well.

Summary of the Manuscript Findings

In the overall context of the dissertation, I tailored my focus to methodological issues related to ecological momentary assessment grounded within the context of the ecological momentary intervention as well as content driven questions that encapsulated aspects of the self-regulation intervention. For the methodological questions that drove the methodological manuscript (Chapter IV), I wanted to explore this methodological approach as it has begun to gain greater traction in the educational community based on having the potential to capture and investigate students' every day experience while being in a moment. I considered factors that may be associated with participants response rates and compliance. First, I found that there was an issue with participant response rates (i.e., participant response rates were approximately 66% across the course of the study). It is hard to know if this number is low with educational contexts given the wide variety of contexts in which participants have been studied using EMA or ESM. For example, in classroom settings, response rates were as low as 48 percent (Dietrich et al., 2017). Response rates for my study are also similar to studies conducted in non-classroom settings (e.g., Beymer et al., 2018). One substantial issue was that no differences were found regarding the probability of non-response across the two conditions. However, there were baseline factors associated with the probability of non-response (e.g., self-control) suggesting the data were not missing completely at random. In the future, intervention development might need to be more directly targeted toward self-control or lack thereof.

I also question methodological considerations regarding times to collect participant data. Regardless of condition, I found a lower likelihood of responding across the weekend. This, coupled with the lower probability of studying over the weekend, brings question as to whether data collection over the weekend is beneficial for investigating study behaviors. The odds of not reporting studying over the weekend compared to weekdays were approximately double. Or this could potentially be a targeted aspect of the intervention to help struggling students realize how they are using their time and bring more awareness to how they could potentially spread out their study sessions across the week and over the weekend. The original intent was to capture any instance of reported studying including weekdays and weekends. Given the sample size in the study (n = 49) as well as the characteristics of the sample, I would not remove data collection over the weekends, but would recommend controlling for weekday versus weekend.

As discussed previously, compliance to instructions was focused on initiation of event-based study sessions by the user when they were engaged in study behaviors. Based upon the researcher generated prompts (RGPs), coupled with the user-initiated prompts regarding study sessions, I saw a discrepancy between RGPs and users initiating the app for study behaviors. With regard to reporting study sessions, there was only one participant who reported significantly more study sessions in the signal-contingent RGPs than what was actually initiated in the user-initiated event-based study sessions. We found more instances where participants completed user-initiated sessions than what were reported on the studying questions in the signal-contingent RGPs, but this could be due to low response rates for the signal-contingent RGPs. Based upon informal responses from participants who did not initiate a study session, one reason mentioned was they forgot to initiate. These missing responses from participants may have contributed to the lack of differences across conditions. An additional reason for missing data or non-compliance for the user-initiated reports could be access to their phones while studying (as was the case with some student-athletes).

I additionally found a discrepancy in reporting study behaviors within the same signal-contingent prompt with participants reporting not studying since the last prompt but then also reporting an amount of time they had spent studying since they were last prompted on the next question in the protocol (22% of the time). With this discrepancy, one wonders what factors might have been at play. Participants may have reconsidered what was meant by studying between the two questions or it worked as a cueing effect and they were reminded of studying between the questions or it could be a constraint of how the question was designed with an amount of time scrollbar that needed to be moved to advance to the next question. I did notice with some of the practice prompting during the baseline appointment that some participants were able to advance without engaging with the prompt (therefore, skipping to the next question). With the discrepancy in reporting of time spent studying and engaging in studying, I had to modify the outcomes of interest addressed in my content-based paper for Q6. With both responses, there were large instances of non-study responses, which further led to the use of a binary outcome over trying to account for time spent studying in minutes.

With regards to the content driven manuscript (Chapter V), I focused on associations of academic motivation and emotions along with their relation to reports of study engagement. I also looked at group differences in the aforementioned relationships between the intervention and assessment-only groups to investigate the use of daily prompts as a way to intervene in students' daily lives. Overall, it appears there was evidence that participants were not regulating their study time in terms of spacing of time as well as amount of time spent studying. In the baseline appointment, over half of the participants reported that they regularly spaced their time studying for a course assessment. With the EMA data, there was large variability in participant study times, with some daily reported instances as high as ten hours. Given the time in the semester, participants may not have perceived the need to study, or they did not have a course assessment or assignment coming up soon. With the end of day reports across all participants, there were only 73 instances where participants reported a course assessment coming up within the next two days. In future research, it might be beneficial to ask participants if they feel a need to study for his/her indicated upcoming course assessment.

Additionally, I found that facets such as academic motivation and negative emotions such as anxiety may need to be monitored to tailor the intervention. I found that fluctuations in anxiety and motivation were negatively associated with reports of studying. For academic anxiety, it could be expected that greater fluctuations might relate negatively to academic motivation and engagement (Dunn, 2014; Legault et al., 2006; Pekrun et al., 2002). Individuals who have higher momentary instances of anxiety, when compared to their overall average (or baseline/ general anxiety level), could view lowering their motivation as a coping mechanism (Arthur, 1998). With regards to motivation, we also saw that fluctuations in EMA reported interest were negatively associated with motivation. Students' interest in academic outcomes and course content may be fluctuating more towards the end of the semester. These patterns would be worth following up in future studies across the semester, as there could be different motives associated with students' academic motivation depending on the period of time within the semester. Further, patterns in academic motivation and emotions may be monitored to see if custom prompting to participants is needed. For example, with advances in technology, participants' response patterns could be monitored, and reminders could be delivered to study if there are large fluctuations in participant response patterns.

When looking at end of day reports of studying and in the moment reports of studying, there was a moderate relationship. This relationship may be attenuated for a number of reasons, which was discussed in chapter IV. There was also a moderate relationship found between planned versus end of day reported studying for the intervention with the same caveats. For the end of the day reports, there was missing planned or end of reported daily study in approximately half of the cases, which can bias the association. Based upon the findings of Ketonen et al. (2018), it would have been beneficial for participants to report motivation for their time-based goals, but this was not addressed to limit participant burden.

Limitations

There were several limitations from this study. The time in which data were collected is associated with results presented in both manuscripts. The data were largely collected during the second half of an academic semester, with approximately one quarter of the participants completing the phone assessments in the two-weeks leading up to finals week. It was the intention to not have data collection at the beginning of the semester when participants did not have their first assessments, or they had not planned their study behaviors for the semester. On the other hand, participants may have already figured out what strategies they needed for the semester or settled into patterns as well as decided that they did not need to study as much during the reporting window due to lack of important course assessments (e.g., tests, quizzes). Also, it could have been too late in the semester to break a pattern of studying that might not have been as conducive for learning, which might be related to the number of participants that would be identified as being on academic probation (due to cumGPA). It would have been beneficial to ask participants at baseline the number of major course assessments they would be taking over the 14-day study period. For the purposes of this study, participants were asked to focus their reports of studying to one course at a time, even when they were sitting to study for multiple courses. This was done to provide some anchoring for participant responses but could have led to underreporting of study instances.

Another possible limitation in the study involved participant technology. In informal interviewing, participants reported instances where they did not receive a phone push notification that a prompt was available to complete. This may result from participants not having notifications turned on for their applications and could be a constraint of technology impacting data collection. Participants stated that they would see a notification icon on the application, but when they entered the application the ability to respond was timed out. An additional limitation related to technology stems from the application in and of itself. For certain questions, participants would have to move a scroll bar off of zero to record a response (if their response was zero, they would have to move the scroll bar off of zero and back to zero). Throughout the course of the study, I noticed that this was not always the case with certain phones (e.g., some Android systems would allow the response to be recorded without engaging with the application except pressing next). This could have led to potential increases in the zero responses found for time spent studying, and time spent engaging in schoolwork. And the opposite could be true, those that needed to move off of the zero and then back (for a zero response) to move to the next question could have led to the discrepancy reported between the binary yes/no question on studying and the amount of time spent studying.

A third limitation includes researcher error in programming, leading to missing data in some versions of the protocol. This was discussed as the missing yoked follow-up sessions for five participants within the intervention condition. Within the study session, participants in the assessment-only condition did not respond to pre-studying self-efficacy, which coupled with the sparseness of user-initiated sessions, prevented the comparison of self-efficacy to positive emotion perceptions when participants responded to the yoked follow-up prompt.

Another possible limitation involves some instances of a reactivity effect. There were instances where participants started a user-initiated event-related study session right after responding to signal-contingent prompts, but this was not always the case. The signal-contingent prompt could have served as a reminder to initiate an event-based study session, but there are questions as to whether the data are from an actual study session, or rather a demand characteristic to initiate. One would feel more inclined to trust the data more from those who initiated at times not following a signal-contingent prompt regarding past behavior. There are several plausible methods to address this issue. One way to address this in addition to checking time stamps for when the event-related session began, factors such as response patterns and time spent in the session could be explored compared to sessions not following a signal contingent prompt. To address participants being able to initiate a study session after a signal contingent prompt, researchers may set parameters in the application for allowing event-related sessions if the technology allows. That is, participants cannot start an event-related session within a certain period of time after receiving a signal contingent prompt. Another possible task is to ask participants if the prompt served as a reminder, but this may be prone to social desirability responding.

Given the participant sample size and missing data, there was also a necessity to change what predictor variables were used in the models. There were several instances of convergence issues with some of the models as intended. I tried to keep the intent of the models in place but was the reason certain models like the academic emotion (Q5) and endorsement of study models (Q6) had fewer predictors.

Future Directions

The next step in this research progression for the content-focused side would be to incorporate perceptions of autonomous and controlled motivation across self-regulation conditions regarding the goal-setting aspects. This was an initial criticism of Ketonen et al. (2018) because they asked participants to report their daily goals. To address this criticism, along with the limitations from my study, I would implore a design where I would have additional groups to address whether there was a presence/absence of daily goal setting and strategy presentation. Within the assessment-only condition, I would continue the protocol of not asking about daily goals. With all conditions, I could monitor their perceptions of autonomous versus controlled motivation within reporting moments, and the relationship to reports of studying. To test the efficacy and effectiveness of the proposed intervention, it would be of benefit to test in samples of new college students both in and not enrolled in first year experience courses, as well as in specific majors with more time studying (e.g., within STEM fields).

As this methodology progresses and the affordances of technology push things forward, there is a greater need to understand nuanced aspects of this approach. I plan to examine further feasibility around how to best capture event-related student study behaviors and whether there is benefit in incorporating signal contingent reminders for user-initiated sessions. For example, participants may receive a reminder after starting a user-initiated session to complete the end of study report if they have finished studying.

In the current study, participants were sent reminders to complete signal-contingent responses after thirty minutes, but there were no reminders for engaging in the event-related study sessions. While the technology did not allow reminders directly from the event-related sessions, because participants initiate the sessions on their own, there is a possibility in future work to build in some form of reminder prompt from the signal contingent session. The technology we used was not as adaptive in this aspect. My initial thought was that for the intervention condition the daily goal setting would serve as a reminder for filling out event-related study sessions, but this did not appear to be the case.

Additionally, another line of work I plan to examine involves a focus of participant behaviors towards studying and academic emotions in one particular course (e.g., an introductory biology course), as well as perceptions of students' perceived favorite and least favorite courses for the semester. This would allow for an examination regarding how participants' perceptions of interest direct their study behaviors and engagement within the moment. To do this, I may implore a longer design, but participants will only respond to questions related to those particular courses.

Conclusions

As currently used, the feasibility of using both types of prompting within an educational based intervention was not fully supported, but the insights of using both types of prompting were present. For example, I did see evidence of non-compliance by reports in the signal-contingent researcher-generated prompts. I also saw instances of multiple study session reports between researcher-generated prompts, which would not have been possible if only one type of prompt was presented. There were no differences between conditions with reports of engagement (both as time spent studying or as an indicator of reported study), which suggested a lack of compliance to protocol. This provides a starting point for future research refining use of self-regulatory variables within the moment and refining the duration and quality of gathering data is needed to further evaluate the benefits.

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APPENDIX A

INSTITUTIONAL REVIEW BOARD APPROVAL

UNIVERSITY OF
NORTHERN COLORADO

Institutional Review Board

DATE:	October 22, 2018
TO:	Kerry Duck, MA
FROM:	University of Northern Colorado (UNCO) IRB
PROJECT TITLE:	[1326552-1] Understanding Student Academics using Real-Time Data Collection
SUBMISSION TYPE:	New Project
ACTION:	APPROVED
APPROVAL DATE:	October 22, 2018
EXPIRATION DATE:	October 21, 2019
REVIEW TYPE:	Expedited Review

Thank you for your submission of New Project materials for this project. The University of Northern Colorado (UNCO) IRB has APPROVED your submission. All research must be conducted in accordance with this approved submission.

This submission has received Expedited Review based on applicable federal regulations.

Please remember that informed consent is a process beginning with a description of the project and insurance of participant understanding. Informed consent must continue throughout the project via a dialogue between the researcher and research participant. Federal regulations require that each participant receives a copy of the consent document.

Please note that any revision to previously approved materials must be approved by this committee prior to initiation. Please use the appropriate revision forms for this procedure.

All UNANTICIPATED PROBLEMS involving risks to subjects or others and SERIOUS and UNEXPECTED adverse events must be reported promptly to this office.

All NON-COMPLIANCE issues or COMPLAINTS regarding this project must be reported promptly to this office.

Based on the risks, this project requires continuing review by this committee on an annual basis. Please use the appropriate forms for this procedure. Your documentation for continuing review must be received with sufficient time for review and continued approval before the expiration date of October 21, 2019.

Please note that all research records must be retained for a minimum of three years after the completion of the project.

If you have any questions, please contact Nicole Morse at 970-351-1910 or nicole.morse@unco.edu. Please include your project title and reference number in all correspondence with this committee.

Kerry and Dr. Phillips -

Thank you for both your patience and the exceptionally well-prepared and thorough IRB application for this relevant and meaningful research.

Your protocols and materials have been reviewed and recommended for approval by both Dr. Helm, IRB Member and myself. Best wishes with your research and don't hesitate to contact me with any IRB-related questions or concerns.

Sincerely,

Dr. Megan Stellino, UNC IRB Co-Chair

This letter has been electronically signed in accordance with all applicable regulations, and a copy is retained within University of Northern Colorado (UNCO) IRB's records.

APPENDIX B

INFORMED CONSENT FOR RESEARCH PARTICIPANT POOL

UNIVERSITY OF
NORTHERN COLORADO

Project Title: A Smartphone Investigation of Motivation and Study Strategies

Researcher: Kerry Duck, M.A., School of Psychological Sciences
Phone: 970-351-2869 Email: UNC.Motivation.1@gmail.com

Faculty Advisor: Michael Phillips, Ph.D., School of Psychological Sciences
Phone: 970-351-1296 Email: Michael.Phillips@unco.edu

Purpose and Description: The primary purpose of this study is to examine students' academic motivation and study strategies by having them respond on their smartphones. To be eligible for this study, you must: 1) be an undergraduate student enrolled at the University of Northern Colorado, 2) be at least 18 years of age or older, and 3) have a smart phone with the ability to download applications.

There are two parts in total to this study: 1) An in-person baseline assessment, and 3) a three-week smartphone assessment where you'll receive questions to respond to on your phone.

PART 1: In part one, you will meet one-on-one with a trained researcher for approximately one and a half hours. During this meeting, you will complete a demographic questionnaire, a reading task and assessment which will be audio recorded. You will also complete an interview about your study strategies and a self-report survey of academic motivation and emotions. We will ask that you complete a release of information form (FERPA release) so we can obtain academic records (i.e., GPA, SAT/ACT scores, and any course or university withdrawal) from UNC's registrar office. **During this appointment, we will also ask you to log into URSA** and to verify your recent UNC GPA on your online academic transcript and your current academic course schedule. The research interviewer will record your GPA in the online interview program and will print out your class schedule.

PART 2: Before you leave the lab session, the interviewer will explain the smartphone assessment to you. This part of the study will include messages sent to your phone approximately three times per day over two weeks. When you receive each message, you will need to go to the app and enter your responses. Each message will take approximately one to two minutes to respond. Before you leave the lab session, we will help you download the app to your phone and practice entering your information. In addition to providing responses to specific questions, the app also collects GPS data about your location when you respond. The researchers may link your location to the data you provide but will never disclose this information outside of the study. We will contact you by phone, text, or email several days after this appointment to make sure that the smartphone app is working well for you and to address any concerns.

Please note, standard data charges will apply if you do not have an unlimited data plan on your phone. Students will not be reimbursed for these fees.

Participants will be compensated in two ways for participating in this study based on the required time needed to participate. **Participants will be compensated with 8 research credits for their participation in this study**. **In addition, participants who answer the majority of the prompts in the phone assessment period for part 2 will receive an additional $20 gift card**. You will be provided with the research credit and the $20 gift card after the completion of the three-week smartphone phone assessment. You will need to return to the lab to pick up your gift card at a scheduled time that works for you.

No identifying information about your responses will be provided to anyone outside of this study. We will keep all of your information confidential, or private, by storing it in a locked secure cabinet in McKee 072 or a password protected account on a secure server.

The risks associated with this study are no more than you would experience in everyday life. Your name will not be associated with your data beyond the demographic information you provide on the pre-survey and will be kept separate from your data responses. We will download responses and a unique identifier will be assigned to them. Benefits of the study include potential reflection on how you study, which may lead to a change in your study behaviors and habits.

If you have any questions about the study, please contact us via email or phone as listed above. We will also answer any questions at the in-person appointment.

Participation is voluntary. You may decide not to participate in this study and if you begin participation you may still decide to stop and withdraw at any time. Your decision will be respected and will not result in loss of benefits to which you are otherwise entitled. Having read the above and having had an opportunity to ask any questions, please sign your name and date below if you would like to participate in this research. A copy of this document will be given to you to retain for future reference. If you have any concerns about your selection or treatment as a research participant, please contact Nicole Morse, Research Compliance Manager, Office of Research, 25 Kepner Hall, University of Northern Colorado, Greeley, CO 80639; **970-351-1910**.

____
Printed Full Name of Study Volunteer

____ ____________________
Signature of Study Volunteer Date

____ ____________________

APPENDIX C

INFORMED CONSENT FOR NON-RESEARCH PARTICIPANT POOL

Project Title: A Smartphone Investigation of Motivation and Study Strategies

Researcher: Kerry Duck, M.A., School of Psychological Sciences
Phone: 970-351-2869 Email: UNC.Motivation.1@gmail.com

Faculty Advisor: Michael Phillips, Ph.D., School of Psychological Sciences
Phone: 970-351-1296 Email: Michael.Phillips@unco.edu

Purpose and Description: The primary purpose of this study is to examine students' academic motivation and study strategies by having them respond on their smartphones. To be eligible for this study, you must: 1) be an undergraduate student enrolled at the University of Northern Colorado, 2) be at least 18 years of age or older, and 3) have a smart phone with the ability to download applications.

There are two parts in total to this study: 1) An in-person baseline assessment, and 3) a three-week smartphone assessment where you'll receive questions to respond to on your phone.

PART 1: In part one, you will meet one-on-one with a trained researcher for approximately one and a half hours. During this meeting, you will complete a demographic questionnaire, a reading task and assessment which will be audio recorded. You will also complete an interview about your study strategies and a self-report survey of academic motivation and emotions. We will ask that you complete a release of information form (FERPA release) so we can obtain academic records (i.e., GPA, SAT/ACT scores, and any course or university withdrawal) from UNC's registrar office. **During this appointment, we will also ask you to log into URSA** and to verify your recent UNC GPA on your online academic transcript and your current academic course schedule. The research interviewer will record your GPA in the online interview program and will print out your class schedule.

PART 2: Before you leave the lab session, the interviewer will explain the smartphone assessment to you. This part of the study will include messages sent to your phone approximately three times per day over two weeks. When you receive each message, you will need to go to the app and enter your responses. Each message will take approximately one to two minutes to respond. Before you leave the lab session, we will help you download the app to your phone and practice entering your information. In addition to providing responses to specific questions, the app also collects GPS data about your location when you respond. The researchers may link your location to the data you provide but will never disclose this information outside of the study. We will contact you by phone, text, or email several days after this appointment to make sure that the smartphone app is working well for you and to address any concerns.

Please note, standard data charges will apply if you do not have an unlimited data plan on your phone. Students will not be reimbursed for these fees.

Participants will be financially compensated for their participation. The reimbursement for completing this study will be a gift card. **The amount of the gift card will range from $30-40, depending on how often you respond to the messages.** If you respond to a majority of the messages, you will receive a $40 gift card. If you respond to less than 50% of the prompts over the 3-week period, you will receive $30 for your participation. You will be provided with the gift card after the three-week smartphone assessment. You will need to return to the lab to pick up your gift card at a scheduled time that works for you.

No identifying information about your responses will be provided to anyone outside of this study. We will keep all of your information confidential, or private, by storing it in a locked secure cabinet in McKee 072 or a password protected account on a secure server.

The risks associated with this study are no more than you would experience in everyday life. Your name will not be associated with your data beyond the demographic information you provide on the pre-survey and will be kept separate from your data responses. We will download responses and a unique identifier will be assigned to them. Benefits of the study include potential reflection on how you study, which may lead to a change in your study behaviors and habits.

If you have any questions about the study, please contact us via email or phone as listed above. We will also answer any questions at the in-person appointment.

Participation is voluntary. You may decide not to participate in this study and if you begin participation you may still decide to stop and withdraw at any time. Your decision will be respected and will not result in loss of benefits to which you are otherwise entitled. Having read the above and having had an opportunity to ask any questions, please sign your name and date below if you would like to participate in this research. A copy of this document will be given to you to retain for future reference. If you have any concerns about your selection or treatment as a research participant, please contact Nicole Morse, Research Compliance Manager, Office of Research, 25 Kepner Hall, University of Northern Colorado, Greeley, CO 80639; **970-351-1910**.

____

Printed Full Name of Study Volunteer

____ ____________________

Signature of Study Volunteer Date

____ ____________________

APPENDIX D

EMA/EMI MEASURES

Signal-Contingent sessions (Researcher Generated Prompts)

1) What was the MAIN activity you were doing when we prompted you?
2) Have you studied (any session in which you sat down to prepare for a class which does not result in a direct grade in your class) since the last time you responded to a random prompt? YES/NO

   SKIP LOGIC → YES

   a. Did you initiate a study session in the app? YES/NO

   SKIP LOGIC → NO

   b. Why not?

3) Since the last time we prompted you, estimate how much TIME you spent STUDYING (e.g., reading, outlining, or summarizing class information). Minute selection

4) Since the last time we prompted you, estimate how much TIME you spent doing SCHOOL WORK beyond STUDYING (e.g., writing papers or other assignments). Minute selection

5) How motivated do you currently feel to focus on school work or studying right now? Rate your motivation on a scale from 0 – 10, with 0 being "not at all" and 10 being "extremely motivated."

6) Rate the following based upon how you feel right now about academics using the following scale 1(not at all) to 7 (very much)

   Interested

   Determined

   Anxious

   Irritable

   Stressed

   Bored

Retrospective Recall (end of the day)

7) How much time in total have you spent studying today? Minute selection

8) Did you miss any classes today? YES/NO

   SKIP LOGIC → YES

   a.) How many?
   b.) What classes did you miss (e.g., BIO 110)?

9) Did you have any assessment today (e.g., Quiz/Exam)? YES/NO

10) Did you have any homework/assignments due today (e.g., paper/lab report)? YES/NO

<u>Study Session (User Initiated Prompts) - Control Group only</u>

Studying is defined as any session in which you sit down to prepare for a class by reading, taking notes, practicing information, etc., which does not result in a direct grade in your class (i.e., not turning anything in for a grade, for example a paper). For what course are you primarily going to study for in this study session (e.g., BIO 110)?

1) Have you set a study goal for this session? YES/NO
   SKIP LOGIC → YES
   a. What is it?

2) How confident do you feel that your studying will benefit your learning? (0-100%)

3) How long do you plan to study? Minute selection

4) Do you have an assessment (e.g., quiz/exam) in this course in the next 2 days? YES/NO

5) Do you have an assignment (e.g., paper/lab report) due for this course in the next 2 days? YES/NO

6) Rate the following based upon how you feel right now about academics using the following scale 1(not at all) to 7 (very much)

   Interested

   Determined

   Anxious

   Irritable

   Stressed

   Bored

7) Which environment best describes your current study location?
   Library/computer lab/office
   Coffee shop/restaurant
   Home
   Other (Please describe): _______________

Study Session (User Initiated Prompts) - Intervention Group only

Studying is defined as any session in which you sit down to prepare for a class by reading, taking notes, practicing information, etc., which does not result in a direct grade in your class (i.e., not turning anything in for a grade, for example a paper). For what course are you primarily going to study for in this study session (e.g., BIO 110)?

1) Set a specific goal for this study session. Write your specific goal in the space below.

2) EXAMPLE STRATEGY: One way in which to help with your studies is to find real world connections to the material. While you are studying, try to draw connections to your life with the material.

3) How confident do you feel that your studying will benefit your learning? (0-100%)

4) How long do you plan to study? Minute Selection

5) Do you have an assessment (e.g., quiz/exam) in this course in the next 2 days? YES/NO

6) Do you have an assignment (e.g., paper/worksheet/discussion questions) due for this course in the next 2 days? YES/NO

7) Rate the following based upon how you feel right now about academics using the following scale 1(not at all) to 7 (very much)

   Interested

   Determined

   Anxious

   Irritable

   Stressed

   Bored

8) Which environment best describes your current study location?
   - Library
   - Coffee shop/restaurant
   - Home
   - Other (Please describe): ________________

Study session (30 minutes in)

1) Have you finished studying? YES/NO
   SKIP LOGIC → YES
   a. How long did you spend studying?
   SKIP LOGIC → NO

   b. How much longer do you plan on studying?

2) Did you study alone or with others? ALONE/OTHERS
   SKIP LOGIC → ALONE
   a. Was this material best suited to be studied alone? YES/NO
   SKIP LOGIC → OTHERS
   b. Were you all studying the same topic or different topics? SAME/DIFFERENT

3) How successful have you been in meeting your goal(s) for your study session? (0-100%)
   a. Why?

4) What were the main strategies you used so far in your study session? Check all that apply
   a. Reading the textbook for the first time
   b. Rereading the textbook
   c. Reading notes
   d. Using flashcards
   e. Copying notes
   f. Reading Powerpoints
   g. Watching videos
   h. Highlighting notes
   i. Creating examples
   j. Summarizing information from notes and textbook
   k. Outlining
   l. Highlighting textbook
   m. Self-quizzing
   n. Explaining material to a peer
   o. Other: _______

5) How confident do you feel that what you have studied in the last 30 minutes benefited your learning? (0-100%)

   a. Why?

6) Rate the following based upon how you felt while studying using the following scale 1(not at all) to 7 (very much)

   Interested

   Determined

   Anxious

   Irritable

Stressed

Bored

Intervention first prompt of day

1) Set a goal for how much time in which you plan to study today. Use the number wheel to set your study time. Minute Selection

2) For what classes do you plan on studying today (e.g., BIO 110)?

Intervention last prompt of day

1) Have you identified how much time you will need to study tomorrow? YES/NO
   SKIP LOGIC → YES
   a.) How much time? Minute selection

2) For what classes do you plan on studying tomorrow (e.g., BIO 110)?