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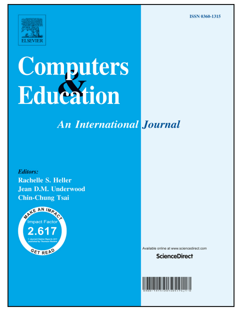

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Affordances of Using Mobile Technology to Support Experience-Sampling Method in Examining College Students' Engagement

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Abstract

In an investigation with 133 undergraduate students, we measured affective, cognitive, behavioral engagement, and self-regulation with a pre-survey, a post-survey, and *in the moment* of studying using experience-sampling methodology (ESM). We compared within these self-report techniques and also between self-reports and objective measures afforded by ESM. We found similar patterns that differed in detail. Furthermore, the ESM surveys allowed for a more fine-grained exploration of engagement related to studying behavior. Importantly, we compared fixed sampling and event-based sampling and found that the latter significantly improved sampling accuracy. Finally, we posit that a new and useful way to assess student self-regulation is the relationship between when students predict that they will study and when students report actual studying in the moment using ESM, which we call implementation rate. We were able to capture and examine all three dimensions of engagement (behavioral, cognitive and affective engagement) and self-regulation in authentic settings and in the same study, allowing us to examine the relationships among these variables exactly when learning occurs, which has several theoretical and practical implications.

Keywords

Engagement; Self-Regulation; Experience-sampling method; Self-report measure; Mobile technology

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1. Introduction

Engagement in academic work is conceptualized as consisting of three key components: Behavioral engagement (e.g., studying and note taking in and out of class), cognitive engagement (e.g., mental effort and thinking strategies), and affective engagement (e.g., valuing, feeling enjoyment or frustration) (Fredricks & McColskey, 2012). Among them, the study of cognitive engagement flourished in the 1990s largely based on self-report survey data (e.g., Entwistle & Entwistle, 1970; Author, 2015a). The instruments were based on information processing research that demonstrated links between types of processing and memory of studied material and the distinction between deep and shallow processing (e.g., Anderson & Reder, 1979; Craik & Lockhart, 1972; Eysenck & Eysenck, 1979). Research has identified important links between types of engagement, self-regulation, motivation, and achievement in academic settings. However, critiques of reliance on self-report data have challenged the continued dependence on these sources that have problems associated with common method bias and social desirability (e.g., Podsakoff, MacKenzie, Lee, & Podsakoff, 2003).

Concerns about people being able to accurately project or retrospect about their behavioral, cognitive, and affective engagement in learning activities encouraged researchers to examine more immediate methods of capturing data on learning. For example, computer-supported learning environments were a convenient platform for capturing data during learning. In these situations, the learning system is programmed to track and record behavioral engagement data, such as time spent and movements made during learning events, often referred to as learning analytics (e.g., Author, 2013b; Siemens, 2013). Researchers are able to examine engagement patterns when students interact with computer or online systems (e.g., Greene & Azevedo, 2010; Winne, 2010). However, students do engage in learning activities for traditional courses that are not mediated through technologies. The learning analytics approach does not afford opportunities to examine these offline learning situations. A variety of other methodologies have been used in educational research, such as eye trackers (Van Den Broek, 2010), galvanic skin response, heart rate and fidgeting indexes (Graesser, 2015), but also have limitations. For example, many physiological instruments are not practical when attempting to investigate college students in the act of studying on their own time and location beyond the laboratory and classroom settings.

In the present study, we examined college students' engagement in study events that are not mediated through technologies, that occurred outside of class, that did not necessarily involve technology. Encouraged by the methods Csikszentmihalyi used to measure flow (Larson & Csikszentmihalyi, 1983), we were interested in how to capture engagement in learning activities in the moment, when students were not in a classroom and learning was not being mediated through computer-based or online systems. We used Experience Sampling Method (ESM), which is a technique used to collect data when people are in an everyday context so that the data reflect what is happening in that moment. ESM involves the use of electronic or digital devices to interrupt people in order to probe their thoughts and feelings in that moment (Larson & Csikszentmihalyi, 1983). Because ESM catches people in the moment of doing something, it can be a more sensitive method of examining thoughts and motivations for learning than traditional self-report measures that rely on either projection (i.e., data gathered before learning events occur) or retrospection (i.e., data gathered after learning events occurred). Given the nearly ubiquitous nature of mobile devices, ESM has become a practical way to capture students' learning, especially college students, outside of classrooms. ESM allows researchers to explore the interaction between students, their context, and their experiences in the moment of learning (Hektner, et al, 2007). The goal of the present study was to examine how experience-sampling method with mobile technology (ESM-Mobile) can support the investigation of college students' engagement in the moment and within the context of authentic learning.

2. Background

2.1. Perspectives on learning engagement

Engagement has been shown to positively impact achievement, motivation, and academic self-concept (Author, 2011, 2013b, 2015b; Fredricks & McCloskey, 2012; Furrer & Skinner, 2003;). Although there is much debate on how to operationalize engagement, we define engagement as being composed of three dimensions including behavioral, cognitive, and affective (Fredricks, Blumenfeld, & Paris, 2004). Furthermore, we suggest that self-regulation is a key component of students' academic engagement. Self-regulation can be cognitive in nature (e.g., monitoring one's understanding; Author, 2015a), but can also include planning and organizing study efforts (e.g., Author, 1996b).

Behavioral engagement has been defined in three ways including positive conduct (Finn & Rock, 1997), involvement in academic tasks (Author, 2013a), and participation in school related activities such as athletics and clubs (Finn & Voelkl, 1993). We focused solely on the second definition, involvement in studying tasks. Behavioral engagement, operationalized as involvement in one's own learning and academic tasks is comprised of several important elements including effort persistence, direction of attention, participation in group work, and self-directed academic behavior (Buhs & Ladd, 2001). Although some of these elements of engagement have cognitive components (e.g., effort persistence and attention also have cognitive manifestations), we look at overt actions when studying the behavioral aspect. For example, in the current project behavioral engagement takes the form of physical studying behaviors that include joining in a study event, being at a location, and choosing a time for studying. These are the aspects of involvement in academic related tasks that we capture. Self-regulation is relevant to behavioral engagement in that students predict times and dates that they can or should study, and thus self-regulate whether or not they actually study during those times.

Cognitive engagement is defined here as using shallow and/or deep learning strategies when studying. Although there are several definitions of cognitive engagement in the literature (e.g., amount of effort, degree of persistence), our interest was in examining students' strategy use in the moment of a particular study event, therefore, our perspective on cognitive engagement was informed by the levels of processing theory posed by Craik and Lockhart (1972) and the research showing that when information was elaborated on using other knowledge, remembering was more successful (e.g., Anderson & Reder, 1979; Craik & Lockhart, 1972). Deep cognitive engagement involves elaboration processes, while shallow involves more rote memorization and other strategies that engage the new information in more superficial ways (e.g., rehearsing and rereading). There is evidence that in learning contexts, a combination of deep and shallow cognitive engagement may be needed (Author, 1996b, 2015a). Importantly, though, there is also evidence that students who struggle sometimes persist in using superficial strategies that do not lead to success (e.g., Author, 2003). Thus, implementing deep and/or shallow processing strategies is a characteristic of self-regulation because students need to regulate their strategic behavior (Author, 1996b).

Affective engagement is defined as students' emotional reactions to academic phenomena such as math specifically or school in general (Pekrun & Linnenbrink-Garcia, 2012; Skinner, Kindermann, & Furrer, 2009). For our purposes, we examined emotions that have been found to be achievement focused (Pekrun & Linnenbrink-Garcia, 2012). We measured positive emotions, such as hope, curiosity, and enjoyment, alongside negative emotions, such as confusion, frustration, boredom, and anxiety. Recent research has shown that emotions are linked to academic achievement via their direct influence on self-regulation (Mega, Ronconi, & Beni, 2014). As expected, negative emotions are negatively linked to self-regulation, while positive emotions are linked in ways that suggest they enhance self-regulation of learning. When students hold negative emotions relative to a learning situation, rather than increasing their regulation toward success in that situation, they direct their attention away from engagement in that learning situation.

We also assessed task-value as a contributing factor to affective engagement (Wigfield & Eccles, 1992). Task-values are defined as the reasons that people have for engaging in a task. Furthermore, task-values are affectively laden because they include emotion such as interest and enjoyment (Author, 2017a). There are three types of values proposed that we included. *Attainment value* is the importance of doing well on a particular task or in a particular context. High attainment value is seen when an individual needs to prove to herself/himself that she/he can be successful. *Intrinsic value* is the enjoyment an individual experiences while engaged in the task. *Future utility value* is the perceived usefulness of completing the task for a future goal. Task-values have been shown to predict task choice and performance in a number of achievement domains (Author, 1999; Eccle et al., 1983; Eccles, 1984; Meece, Wigfield, & Eccles, 1990; DeBacker & Nelson, 1999, 2000; Nolen & Haladyna, 1990; Sullins, Hernandez, Fuller, & Tashiro, 1995). Increased levels of value for schooling have been shown to be linked to increased self-regulation (Pintrich & De Groot, 1990).

As noted above, self-regulation appears to be an important factor to consider when investigating engagement while studying. We define self-regulation as the intentional planning, monitoring, evaluating, and modification of progress towards goals (Zimmerman & Martinez-Pons, 1990). When students set goals for studying, they use self-regulation to achieve their studying goals. For example, students may have a goal of studying for a certain number of hours in the library during the weekend and whether they achieve this predetermined goal is based on their self-regulatory behavior. Thus, behavioral, cognitive, and affective engagement related to studying behavior is related to student self-regulation. In the current study, we investigated students' reports of engagement before, during, and after studying. We also examined students' planned study engagement behaviors as compared to their actual study behavior using ESM, what we call *implementation rate*. More specifically, in our study implementation rate is the relationship between when and where students planned to study, and when and where they actually studied. We posit that this relationship or, implementation rate, is likely an indicator of students' self-regulation with regard to their engagement in studying behaviors. An important goal of the study was to examine how ESM could be used to measure engagement when students are learning outside of class through their studying behavior.

2.2. Perspectives on experience-sampling method

Ample research has shown links between behavioral, cognitive, and affective engagement using self-report measures (e.g., Author, 1996a, 2004; Pintrich and DeGroot, 1990; Pintrich & Garcia, 1991). We wanted to expand on this research and respond to the critiques concerning the sole reliance on self-report data (e.g., Chan, 2009, Hadwin et al., 2001, Rubie-Davies & Hattie, 2012). Scholars have been advocating for the use of additional measures that may replace, or at least support, traditional self-report questionnaires (e.g., Fulmer & Frijters, 2009; Graesser, 2015). One of these concerns can be addressed with the experience-sampling method (ESM). For example, self-report measures typically ask participants to respond to contextually dependent questions, however this occurs after the participant is no longer within the context of interest, which can compromise the validity of responses (Hektner, Schmidt, & Csikszentmihayli, 2007). ESM occurs when repeated self-report is administered and gathered in the moment using some kind of electronic or digital notification system such as pagers, texts, or mobile device applications (Csikszentmihalyi & Larson, 1987).

Because ESM collects data in the moment and in the context of learning, the students are still in the proximity of time and space, they would be more sensitive to the survey questions and would require less cognitive resources to accurately reflect on their cognition and affection (Csikszentmihalyi & Larson, 2014). Therefore, the quality of ESM data should be better than the data collected in prospection and retrospection, although ESM still involves forms of self-report. We think the work of Schmidt and colleagues supports this view (Schmidt et al., 2015; Shumow et al., 2013; 2008). In a collection of studies, Schmidt and colleagues (Schmidt et al., 2015; Shumow et al., 2013; 2008) discovered a more nuanced view of student cognition and motivation during the process of learning. For example, using ESM with middle-school students, the researchers found that students were more intrinsically motivated and in control of their own learning when reading outside of school and more involved and goal directed when reading in school (Shumow et al., 2008). ESM allowed for a more fine-grained understanding of motivational differences between contexts that would have been difficult to achieve using prospection or retrospection. In another study Shumow, Schmidt, and Zaleski (2013) used ESM to investigate the motivation of high-school science students while engaging in laboratory activities as compared to other classroom activities. They found that students had less engagement, lower relevance, and higher enjoyment while engaging in labs. Using ESM allowed for collecting data in the moment of each of these activities, and in turn a more in depth understanding of how students experience each activity comparatively. Relying on retrospection may convolute the results due to the temporal distance between activities and data collection, which could reduce the reliability of the results as compared to the in the moment nature of ESM. Finally, Schmidt and colleagues (2015) explored the association between ethnicity and perceived engagement and competence in high-school science students in the moment of engaging in science activities. Results revealed that Hispanic and non-Hispanic white students responded to different aspects of the learning environment in relation to engagement and competence. ESM allowed the researchers to investigate individual differences in direct response to features of the learning environment, which would be more challenging using prospective or retrospective assessment techniques. Each of these studies provide examples of how ESM can provide researchers with a more pointed examination of the variables of intertest as compared to traditional instrumentation approaches.

There are three main types of sampling techniques when using ESM including random sampling, fixed sampling, and event-based sampling (Zirkel, Garcia, & Murphy, 2015). In random sampling participants are assessed randomly throughout a given data collection period. Whereas in fixed sampling participants are asked to respond to questionnaires at set time points throughout a day or a week. Finally, event-based sampling occurs when researchers ask participants to respond to questions during or after specific events such as a studying session.

Traditional ESM research can be labor-intensive and expensive for both participants and researchers (Zirkel, Garcia, & Murphy, 2015). For example, participation in ESM can be time-consuming and requires a high level of commitment from the participants. Participants in ESM usually have to carry survey packages and respond to them every time they receive beeps from a device with an alarm providing the beep. The researchers have to manage the survey packages, program the alarming devices, monitor the ESM data collection and troubleshoot. With these constraints, therefore, most studies that implemented ESM methodologies to explore engagement are limited to within classroom contexts (Schmidt, Kackar-Cam, Strati, & Shumow, 2015; Shumow, L., Schmidt, J. A., & Zaleski,2013; Shumow, Schmidt, & Kackar, 2008). Little research has used ESM instrumentation to investigate engagement in studying behavior during students' out-of-class experience. With mobile technology permeating almost every aspect of our daily lives, students can use mobile devices to support their learning and performance both inside and outside the classroom (Author, 2017b; Martin & Ertzberger, 2013). These widely accessible mobile devices, and the connectivity of them with databases, bring new opportunities for ESM research. Thus, in this present study, we used Apple iPads to implement ESM instrumentation to examine students' learning engagement and self-regulation within out-of-classroom contexts.

To examine the affordances of mobile technology, we designed two methods for ESM. The first method was a fixed sampling delivered through a combination of Qualtrics® and Remind®. We surveyed the participants to determine high probability times to catch their studying events, and then set up a fixed schedule of 30 occasions across two weeks of the semester (3 times a day for 5 days) in Remind® – an online text-messaging program that allowed us to set up text reminders with links to the mini-surveys that were built in Qualtrics®. Students received text prompts with the survey link. This method uses existing technology resources that are readily available. The second method was event-based sampling. We developed an iPad app specifically to deliver the ESM (see screenshots in Figure 1). Students set up their own study events in a calendar and the app prompted them to answer the mini-surveys during those study events. The app also features location detection and recording, as well as, offline data collection, where students can complete the sampling surveys at locations without an Internet connection.

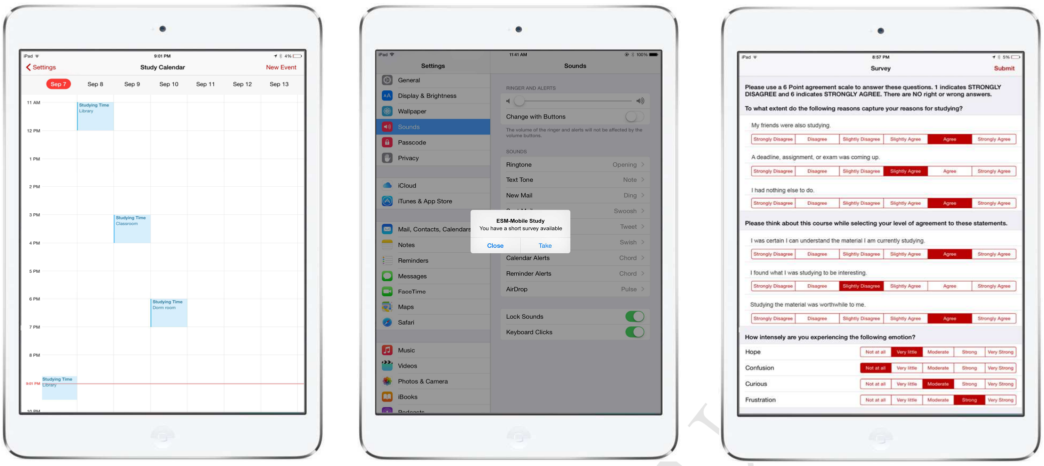


Figure 1. *Screenshots of ESM-Mobile app for event-based sampling (event calendar, prompt, and ESM survey)*

The present study investigated how mobile technology can support experience-sampling method in examining college students' learning habits. There were two main research questions:

1) Is there novel information gained about engagement if we measure aspects of engagement in the moment of studying? This first question had three sub-questions:

   a) Are there differences between students' self-reported plans for studying and their actual behavioral engagement reflected by their study times?

   b) Are there differences between students' responses to affective and cognitive engagement scales (values and learning strategies) when the measures are taken prior to studying (pre), during studying (in the moment), and after the last exam (post or retrospective responses)?

   c) Are there theoretically consistent relationships among the ESM measures and relationships between the ESM measures of achievement?

2) How do fixed sampling and event-based sampling compare in terms of the effectiveness and efficiency of capturing information about students' learning engagement using experience-sampling methods? The second main question had five sub-questions:
   a) Which sampling method has higher response rate and/or capturing rate?
   b) Which sampling method has faster response time and/or longer time on task?
   c) What are the favorite study time and location for college students?
   d) Did students study during the time and location as they planned?
   e) How does students' self-regulation of learning relate to their cognitive and affective engagement based on ESM-Mobile?

3. Method

3.1. Participants

One hundred and thirty-three students, who were pre-service teachers enrolled in educational psychology classes at a large US University, volunteered to participate in this study across two semesters. One-hundred and ten were female and 114 were Caucasian. Most (85%) were between the ages of 19 and 21. These demographics are typical of the teacher education program in which these students were enrolled. Students completed the study for course credit. In accordance with local guidelines for Human Subjects Protection, students were offered alternative activities for earning the research credits.

3.2. Measures

We had measures of affective engagement (valuing and emotion) and cognitive engagement that were taken early in the semester (pretest), in the moment of studying (ESM) and at the end of the semester (posttest). These used a six-point agreement scale (1= strongly disagree and 6 = strongly agree). We also used scores on a midterm exam as an indicator of course achievement.

In the pretest and posttest, we included valuing and cognitive engagement items. The valuing items were based on Expectancy-Value Theory (Wigfield & Eccles, 1992) with two items each for attainment (Studying this material is worthwhile to me), intrinsic (I like what we are learning in this class), and future utility (I am studying now because my achievement plays a role in reaching my future goals). Two aspects of cognitive engagement were measured: Deep (5 items) and shallow (5 items) approaches to studying. An example item for deep engagement was “When learning new material, I summarized it in my own words,” while an example item for shallow engagement was “I study ideas exactly as they were stated in class or in my readings.” These items were from research by Author (1996a), Entwistle and Entwistle (1970), Entwistle and Ramsden (1982), Kardash and Amlund (1991), and Pintrich and De Groot (1990). The reliability estimates were acceptable for the variables measured at pre and post. They varied from a low of .65 for pretest Future Utility valuing to a high of .92 with the majority being .74 or greater.

For the ESM measures, students received a text-based prompt that asked if they were studying or not. If yes, then questions about their reasons for studying followed. We also asked them what they were studying. Next there were two items from each of the following engagement constructs: Self-regulation, deep strategy use, and shallow strategy use. The cognitive engagement items came from the same sources as the pre-post measures noted above. The self-regulation items were from the work of Zimmerman and Martinez-Pons (1990) and had been used in Author (1996a). An example item was “I have a clear idea of what I am trying to learn or accomplish.” Emotions were the other aspect of affective engagement that we measured in the moment of studying using the prompt "How intensely are you experiencing the following emotion?" The prompt was followed by four of the following emotions: Boredom, Enjoyment, Anxiety, Hope, Confusion, Curiosity, and Frustration (Broughton, Sinatra, & Nussbaum, 2013; Pekrun, Goetz, Frenzel, Barchfeld, & Perry, 2011).

3.3. Study context and procedure

We used Qualtrics® for the pretest and posttest surveys in both semesters. In the fall semester, the fixed sampling method was administered. In the spring semester, the event-based sampling method was administered. Students were given iPads when they began the teacher education program, which facilitated the use of ESM methodology. For the ESM measures, we first asked if they were studying or not. If yes, then questions about their reasons for studying followed. Then we asked about details of their studying behavior. We had two forms of the ESM measure with items that had been taken from the measures described above. For a given form, there was one item each for deep and shallow strategy use and a set of four emotions. Scores were averaged across the number of studying events for each person to obtain an in the moment mean for each construct of interest. This was done because the number of studying events captured varied from 1 to 11, with most people having only two studying events.

4. Results

4.1. Comparison between prospective, retrospective and in the moment responses

Are there differences between students' retrospective responses and their actual study time? We first compared students' self-reported plans for studying with the actual study time being captured with the app in the event-based sampling. In the pre-survey, students ranked their most-likely study day and time. We then counted the number of actual study times being captured with the app across the two weeks of data collection period. The results (Table 1 and 2) suggest that self-reported study times and actual study times have similar patterns: Students' study times were more heavily loaded at the beginning of the week and declined toward the weekend. Students' study times were more heavily loaded in the afternoons and evenings as compared to other times of the day. However, there were differences between the self-reported and their actual study times. For example, students reported higher probability of studying on Saturdays and Sundays than they actually did. In addition, the data captured by ESM app provide more fine-grain details of student study times, which can be presented by days, hours, and even minutes, representing the temporal patterns of students' behavioral engagement (see Figure 2).

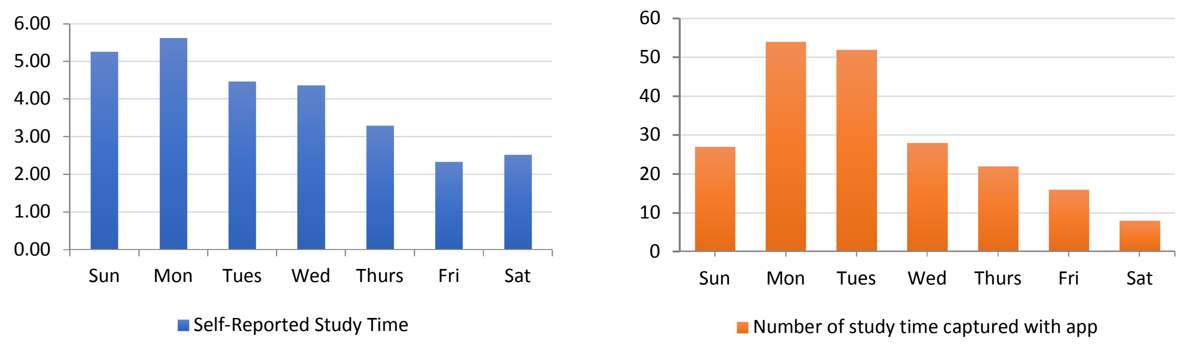
Table 1. *Favorite day for study*

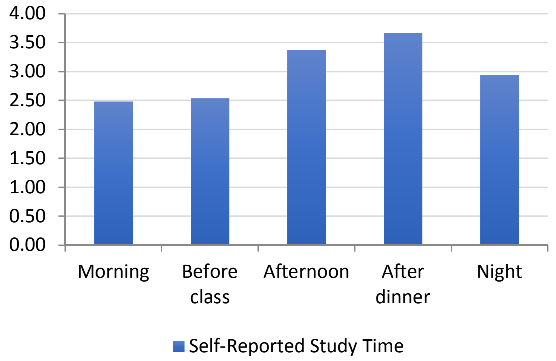
		Sun	Mon	Tues	Wed	Thurs	Fri	Sat
Self-reported Study Time	Average Ranking	5.29	5.66	4.48	4.35	3.3	2.35	2.57
	SD	1.74	1.56	1.56	1.42	1.48	1.44	1.98
Number of study time captured with app		27	54	52	28	22	16	8

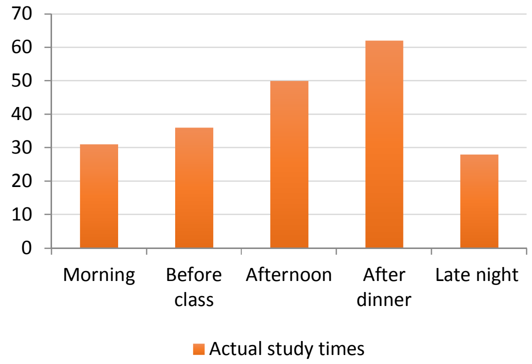
Table 2. *Self-reported preferred study time*

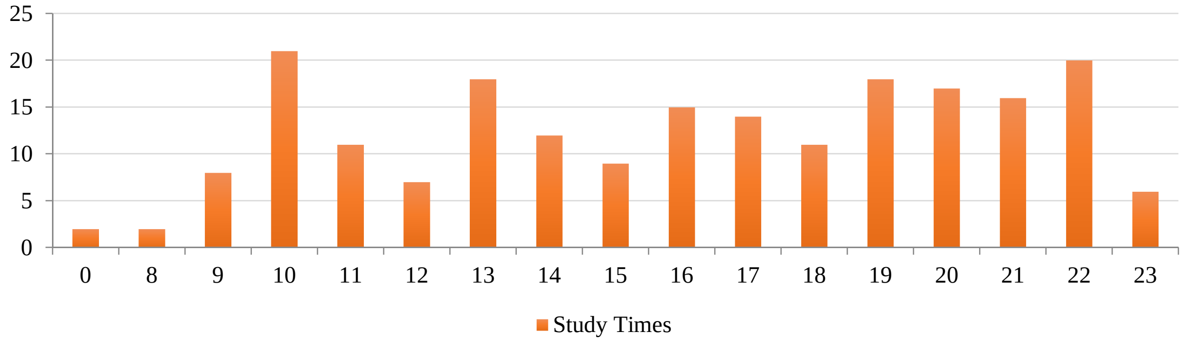
	Morning			Before class			Afternoon				After dinner				Late night		
	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
Average ranking (SD)	2.48 (1.31)			2.54 (1.30)			3.37 (1.36)				3.67 (1.31)				2.94 (1.42)		
Actual study times	31			36			50				62				28		
Study time by hour	2	8	21	11	7	18	12	9	15	14	11	18	17	16	20	6	2

Figure 2. *Study time by weekday, time, and hour*









Are there differences between students' prospective, in the moment, and retrospective responses to affective and cognitive engagement scales? We first performed independent t-tests on the pre-test scores for valuing and cognitive engagement comparing the fixed sampling and the event-based sampling methods. No statistical significances were found, indicating that students' characteristics were similar in these two conditions, therefore, we combined the dataset for the following analyses. We then compared students' prospective and retrospective responses with their responses in the moment while they were studying. We conducted repeated measures tests of mean differences over time (pretest, ESM/in-the- moment measures, and posttest) on students' responses on attainment, intrinsic, and future utility values, and their deep and shallow study strategies. There were no statistical differences for future utility valuing or deep processing. The participants had relatively high means on those measures across time. Significant effects for time were found for attainment valuing [Greenhouse-Geisser $F(2, 187) = 4.95$, $p < 0.01$, partial $\eta^2 = 0.05$], intrinsic valuing [$F(2, 210) = 8.28$, $p < .0001$, partial $\eta^2 = 0.07$] and shallow processing [$F(2, 202) = 16.01$, $p < .0001$, partial $\eta^2 = 0.14$]. Results from Bonferroni tests of specific mean differences are shown in Table 3. For attainment valuing, the mean for in the moment was lower than the pre-mean, but not statistically different from the post-mean. For intrinsic valuing, the means at pre and post were higher than the means for the in the moment measures. For shallow processing, the mean for in the moment was higher than either the pre or post means.

Table 3. *Means and standard deviations for pre, in the moment, and post measures*

		Pre		In the Moment		Post	
Variable	*N*	*Mean*	*SD*	*Mean*	*SD*	*Mean*	*SD*
Attainment value	102	4.96 [a]	.69	4.69[b]	.90	4.84[ab]	.77
Intrinsic value	106	4.57 [a]	.75	4.23 [b]	.96	4.56 [a]	.85
Future Utility value	102	4.98	.61	4.77	.88	4.98	.65
Deep	91	4.88	1.04	4.75	.59	4.71	1.06
Shallow	102	4.37 [a]	1.19	4.86 [b]	.82	4.03[a]	1.30

Note: Means with different superscripts were statistically different using Bonferroni test for pairwise comparisons

Are there theoretically consistent relationships among the ESM measures and relationships between the ESM measures of achievement? A significant challenge that we encountered in collecting ESM data was low response rates in some participants, which resulted in decreased statistical power. Therefore, we only examined bivariate correlations, although we had intended to use regression methods. In regard to the correlations, we can see from Table 4 that there are theoretically consistent correlations among the affective and cognitive engagement variables. For example, attainment and intrinsic valuing were positively related to deep processing, self-regulation, enjoyment, hope, while negatively related to boredom and frustration. We can see that boredom, anxiety, confusion, and frustration all show positive correlations with shallow processing, while enjoyment and curiosity were related to deep processing. Confusion and frustration are negatively related to quite a few of the positive engagement variables, while positively related to boredom. These inter-correlations were largely consistent with theoretical expectations and therefore provide some validity evidence for these in- the-moment measures.

Table 4. *Correlations among in-the- moment measures of affective and cognitive engagement*

In the moment Variable	*Exam*	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*	*11*	*12*
1. Attainment	.22*	1.0											
2. Intrinsic	.32**	.80**	1.0										
3. Future Utility	.09	.36**	.24	1.0									
4. Deep	-.02	.31*	.43**	.16	1.0								
5. Shallow	-.09	-.20	-.05	-.03	.27*	1.0							
6. Self-Regulation	.07	.56**	.53**	.07	.27*	.06	1.0						
7. Boredom	-.25*	-.64**	-.60**	-.19	-.07	.50**	-.22	1.0					
8. Enjoyment	.22*	.42**	.70**	-.08	.30*	.21	.29*	-.34**	1.0				
9. Anxiety	-.17	-.25*	-.09	-.21	-.01	.36**	-.16	.29*	.18	1.0			
10. Hope	.04	.33*	.50**	-.12	.23	.32*	.52**	.03	.48**	.13	1.0		
11. Confusion	-.08	-.52**	-.35**	-.23	-.18	.39**	-.38**	.56**	-.11	.51**	-.04	1.0	
12. Curiosity	.27*	.18	.48**	-.10	.27*	.01	.15	-.10	.57**	.11	.35**	.06	1.0
13. Frustration	-.15	-.70**	-.56**	-.27*	-.25*	.37**	-.42**	.66**	-.15	.54**	-.20	.76**	-.09

Note: Listwise N = 67 for motivation and 63 for emotion variables; * = p < .05; ** = p < .01

The correlations with exam performance demonstrate that measures of positive affect, as measured by attainment and intrinsic valuing and enjoyment and curiosity, are positively related to achievement. Boredom was the negative emotion that correlated negatively to exam performance. The cognitive engagement variables and self-regulation were not related to exam scores as we would theoretically expect, but they otherwise had theoretically consistent relationships (as noted above).

4.2. Comparison between fixed sampling and event-based sampling

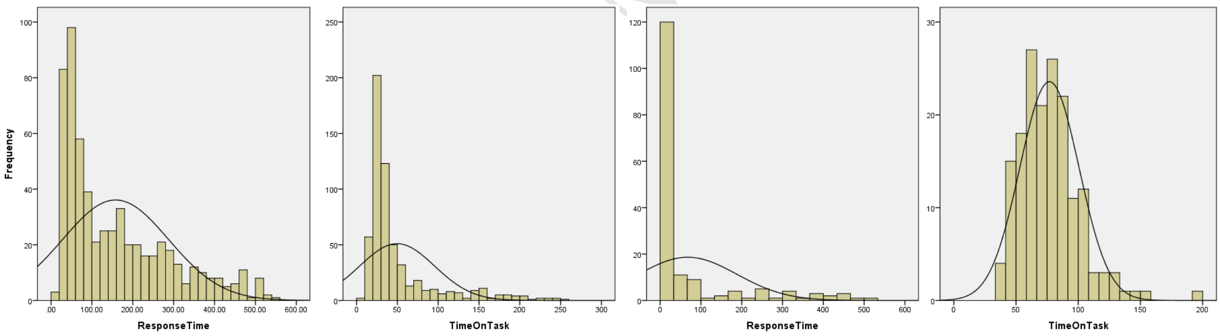
Which sampling method has higher response rate and/or capturing rate? We compared the data from fixed sampling and event-based sampling methods (Table 5). The two methods had similar response rates (69.5% and 68.1%) and captured equivalent numbers of study events (182 and 183). However, the event-based sampling had much higher capturing rate (84.7%) as compared to the fixed sampling (13.0%). A total of 317 prompts were administered in the event-based sampling as compared to 2010 prompts in the fixed sampling, which means the event-based sampling significantly improved the sampling accuracy and reduced extraneous prompts and responses that were delivered at the wrong time and date. In addition, there were 43 (3.1%) missing cases in the fixed sampling. These missing cases were students entered their ID's in the survey but did not answer any questions. There were no missing cases in the event-based sampling.

Which sampling method has faster response time and/or longer time on task? To compare the response speed and time on task, we first removed extreme cases (those that exceeded two SD's). Table 5 describes the results and Figure 2 shows the distribution of the data. The results indicate that event-based sampling had faster response speeds (67.5 seconds vs. 158.2 seconds). Students spent longer time in responding to the event-based mini-surveys (76.9 seconds vs. 49.6 seconds).

Table 5. *Comparison between fixed sampling and event-based sampling*

	Fixed Sampling	Event-based Sampling
Total number of participants	67	66
Total number of prompts	2010	317
Total responses (Response rate)	1396 (69.5%)	216 (68.1%)
Study events captured (Capturing rate)	182 (13.0%)	183 (84.7%)
Non-study time (Non-capturing rate)	1171 (83.9%)	33 (15.3%)
Missing data	43 (3.1%)	0
Total non-responses (non-response rate)	614 (30.5%)	101 (31.9%)
Speed of response	Range: 19-547 seconds M (SD): 158.2 (129.7)	Range: 3-522 seconds M (SD): 67.5 (120.6)
Time on task in completing ESM	Range: 3-253 M (SD): 49.6 (45.9)	Range: 36-197 seconds M (SD): 76.9 (23.8)

Figure 3. *Distribution of response speed and time on task across fixed and event-based sampling*



a. Fixed sampling (response speed & time on task) b. Event based sampling (response speed & time on task)

4.3. Examination of students' engagement using ESM-Mobile

What are the favorite study times and locations for college students? We analyzed the event-based sampling data to identify students' study times and locations. Results show that Mondays and Tuesdays are most popular study days for these college students. Their tendency to study decreases as the week goes on. Within days, studying times spread out except that students were less likely to study during early mornings. With the GPS capacity of our ESM-Mobile app, we were able to collect the geographical locations where students actually studied. Figure 4 shows a heat map of student study locations on campus – a spatial representation of students' behavioral engagement of studying. Results also show that home, apartment and campus buildings were the most popular study locations. Over 90% of the study events happened in these locations. Among campus locations, the library (n=23), student union (n=6), and the college of education building (n=10) were the most popular locations.

Did students study during the times and locations as they planned? We created two new variables to represent how well students implemented their plans regarding study time and location. These analyses were performed only with the event-based sampling data because only the event-based sampling method was able to capture students' study plans as well as their actual study time and location, which would then allow us to calculate the implementation rates. The specific calculation formulas are as following:

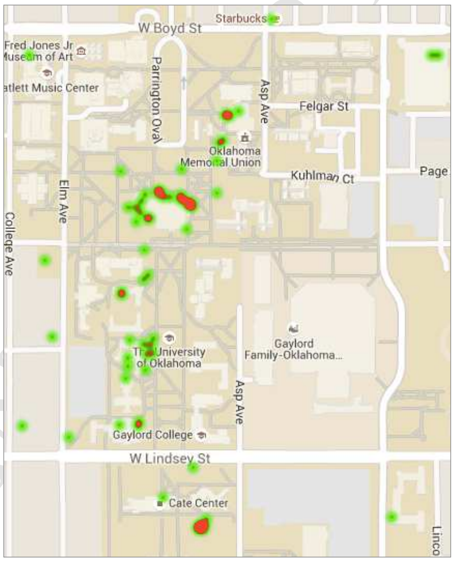


Figure 4. *Heat map of study locations on campus*

$$\textit{Implementation rate of study time} = \frac{\textit{Number of study events captured by ESM}}{\textit{Total number of planned study events}}$$

$$\textit{Implementation rate of study location} = \frac{\textit{Number of study events captured by ESM at the matched location}}{\textit{Number of planned study events at a planned location}}$$

These results are described in Tables 6, 7 and 8. In terms of study time, the results showed that students were better able to follow their study plan during earlier days of the week. The most predictable study day was Monday. Students were least able to follow their plans when they planned to study on Fridays. Within a particular day, students' implementation rate increased as the day went on (Figure 5). The most predictable study time was late at night. Students were least able to stick with their plan when they planned to study in the early mornings.

In terms of study locations, students were most likely to stick with their study plan when they chose home or coffee shops as their study location. When students planned to study at work locations they were mostly likely to change their plan (Figure 6).

Table 6. *Study Time Plan and Implementation by Weekday*

	Sunday	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday
Study Time	27	55	42	25	19	8	7
Not Studying	5	2	11	5	5	4	2
No Response	15	12	19	20	15	13	7
Implement Rate	57.4%	79.7%	58.3%	50.0%	48.7%	32.0%	43.8%

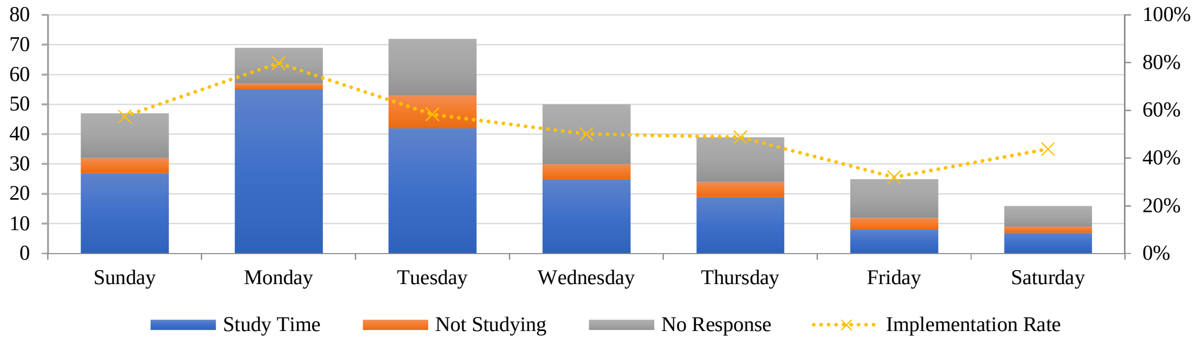
Table 7. *Study Time Plan and Implementation by Time*

	Early morning			Morning			Lunch			Afternoon			Early evening			Night		
	00	07	08	09	10	11	12	13	14	15	16	17	18	19	20	21	22	23
Study Time		3			34			21			47			46			22	
Not Studying		2			5			2			17			5			3	
No Response		3			18			17			30			29			4	
Implement Rate		37.5%			59.6%			52.5%			50.0%			57.5%			75.9%	
Study Time	1		2	9	21	4	8	13	11	10	13	13	7	16	16	17	18	4
Not Studying			2	2		3		2	5	7	3	2	2	2	1		2	1
No Response		1	2	4	7	7	11	6	5	6	4	15	3	8	10	8	3	1
Implement Rate	100%	0%	33%	60%	75%	29%	42%	62%	52%	44%	65%	43%	58%	62%	59%	68%	78%	67%

Table 8. *Study Location Plan and Implementation*

	Planned Location		Actual Location		Matched	
	N	%	N	%	N	%
1. Home/Apartment	101	59.8%	104	61.5%	92	91.1%
2. Campus Building	48	28.4%	49	29.0%	31	64.6%
3. Office/Work	5	3.0%	1	0.6%	1	20.0%
4. Coffee shop	8	4.7%	8	4.7%	7	87.5%
5. Church	2	1.2%	2	1.2%	1	50.0%
6. Friend's House/Apartment	4	2.4%	3	1.8%	3	75.0%
7. Other	1	0.6%	2	1.2%	0	0.0%

Figure 5. *Study Time Plan and Implementation by Day, Time, and Hour*



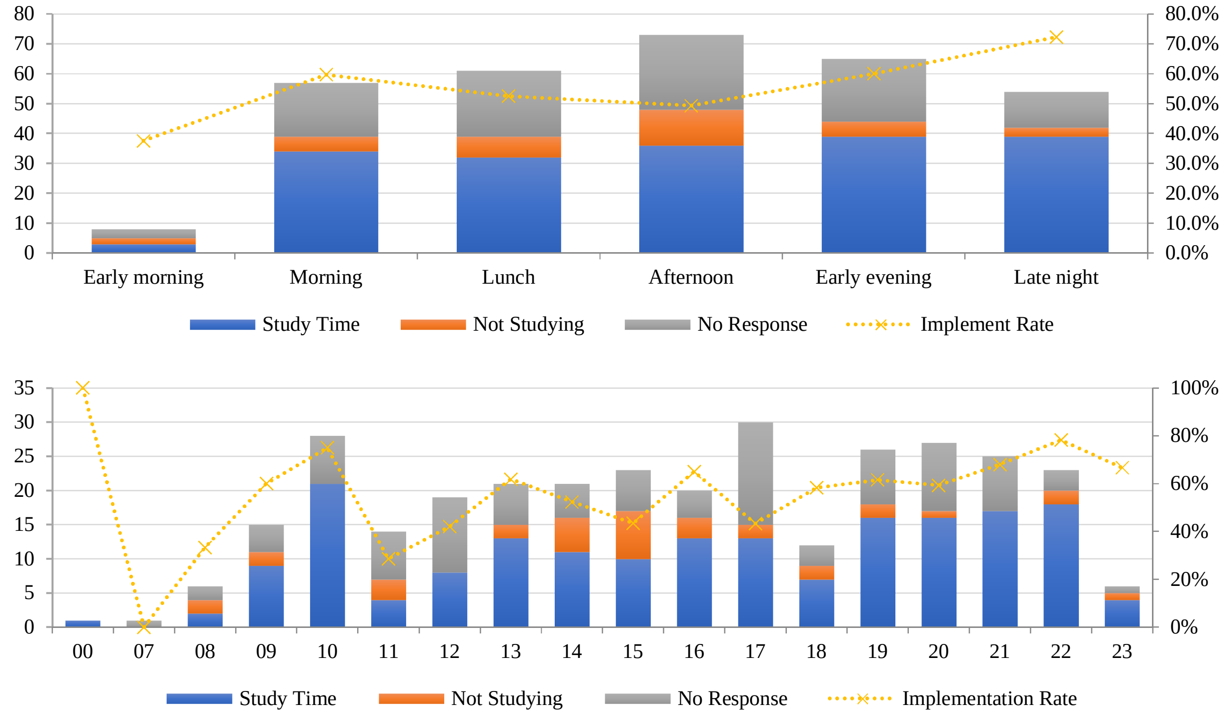
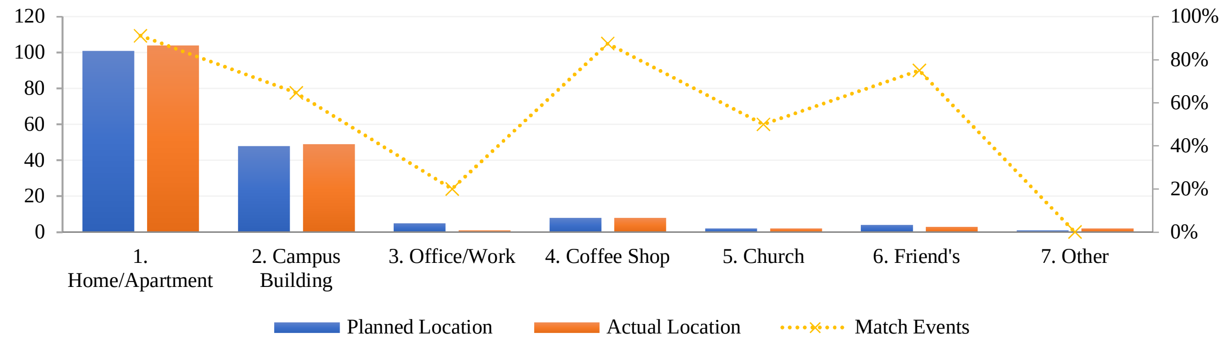


Figure 6. *Study Location Plan and Implementation*



How does students' self-regulation of learning relate to their cognitive and affective engagement based on ESM-Mobile? This final set of correlation analyses was based on the event-based sampling data only. We examined bivariate correlations among the self-regulation variables and students' cognitive and affective engagement in studying. This set of analyses is unique because students' self-regulation is represented by not only the implementation rate of time and location which were calculated upon the planned events and actual study events, but also students' self-report of their self-regulation of learning in the moment of their studying event. The correlations between students' self-regulation variables (i.e., implementation-time, implementation-location, self-regulation), cognitive engagement variables (i.e., deep and shallow strategies), and affective engagement (including values and emotions) are presented in Table 9. The results showed a strong correlation between implementation rates of time and location, but no significant correlation was found between the self-reported self-regulation and our calculated self-regulation measures. Strong correlation patterns were found between self-reported self-regulation and affective engagement variables in the moment. Overall, students reported that they were more self-regulatory in their learning when they held more positive values toward learning, and when they experienced more positive emotions and less negative emotions in the moment of studying. Implementation rate of time was negatively correlated with utility value (which was not expected) and frustration. Implementation rate of location was positively correlated with hope but negatively correlated with frustration. No significant correlations were found between self-regulation and cognitive engagement variables, but lack of power due to the small N might explain the .27 correlation between self-regulation and deep not being significant.

Table 9. *Correlations between self-regulation, cognitive and affective engagement in the moment*

	1	2	3
1. Implementation-time	1		
2. Implementation-location	.76**	1	
3. Self-regulation	.15	.14	1
4. Deep strategies	.18	.13	.27
5. Shallow strategies	-.08	-.05	-.09
6. Intrinsic value	.06	.01	.59**
7. Attainment value	.07	.09	.63**
8. Utility value	-.32*	-.25	.04
9. Curious	.08	.08	.10
10. Enjoyment	.13	.09	.44**
11. Hope	.19	.33*	.67**
12. Anxiety	-.28	-.00	-.18
13. Boredom	-.17	-.18	-.39*
14. Confusion	-.28	-.28	-.49**
15. Frustrate	-.43**	-.51**	-.58**

Note: Listwise N = 41; * = p < .05; ** = p < .01

5. Discussion

In the current study, we examined students' engagement in study activities in contexts where learning was not necessarily mediated through technologies and where learning occurred in authentic out-of-classroom settings. We were particularly interested to examine the affordances of mobile technology in supporting the experience-sampling methodology (ESM-Mobile) in which the research data were collected in the moment and context of learning. We designed and tested two types of sampling methods with combinations of existing and self-developed technological tools.

The findings suggest that ESM-Mobile offers a variety of advancement in educational research moving beyond the prospective and retrospective self-report methods. First, ESM-Mobile offers fine-grained data collection on students' learning engagement. With such fine-grained data, researchers are able to examine engagement more concisely. For example, in the current study, we were able to provide both temporal and spatial visual representations of behavioral engagement. Figure 2 presents the temporal patterns of students' behavioral engagement, and Figure 4 presents the spatial patterns of students' behavioral engagement. These fine-grained data also provide flexibility in terms of how researchers process and use them for analyses. For example, in our study we aggregated the ESM data by week, by day, and by hour. Had we captured more study events in the current project, we would also be able to build longitudinal models of students' engagement. This could be a direction for future studies using ESM in examining engagement. Second, ESM-Mobile collects a combination of self-reported data (e.g., emotion, study strategies) and objective data (e.g., study time and location). Because these self-reported data are naturally linked to the objective data during the data collection, they allow researchers to examine new research questions or even new variables. In the current study, we were able to capture and examine all three dimensions of engagement (behavioral, cognitive and affective engagement) and self-regulation in authentic settings and in the same study, allowing us to examine the relationships among these variables exactly when learning occurs, which had been acknowledged in the literature to be challenging (Zirkel, Garcia, & Murphy, 2015). We were able to create two new variables – the implementation rate of study time and the implementation rate of study location – as a form of evidence for students' self-regulation of their study. In combination with self-reported self-regulation measures in the moment, we added more comprehensive perspectives for the examination of the relationships between self-regulation and engagement – a major contribution to address issues of the solo reliance on self-reported measures in educational psychology research.

The current findings suggest that there were no major differences between the ESM objective data and their retrospective self-reports on behavioral engagement. In general, students in this sample spent more time on studying earlier in the week and declined their study as the week moves forward. They increased their learning activities during a day and slightly declined during late night. Also, they tended to choose to study at home, in their apartment, or campus building (see Table 8). However, the findings offer new insights to students' behavioral engagement beyond retrospective self-report. For example, students often overestimate the time they spend on studying for Saturdays and also late nights. Students' behavioral engagement often peaks at 10:00, 13:00, 19:00, and 22:00 (see Figure 2).

The study results also suggest that there were not major differences between in the moment self-reported engagement and the more traditional prospective or retrospective measures, but we did find important, nuanced differences. When we look at the means shown in Table 4, we can see that the trend for valuing and cognitive engagement in the moment are consistently lower, except for shallow engagement, which was higher. The results suggest that students tended to report more desired outcomes in prospection and retrospection than their responses in the moment. One way to interpret these trends is that the increased proximity of time and space bought by the ESM-Mobile might have reduced the social desirability in students' responses, while social desirability is a common methodological issue for prospective and retrospective self-reports (Scollon, Prieto, & Diener, 2009).

From the relationships between cognitive and affective engagement and exam performance we can see that positive affect is important within this learning context. More specifically, values, especially attainment and intrinsic valuing, are positively linked to deep strategies, positive emotions, and negatively associated with negative emotions. Positive emotions (e.g., enjoyment and curiosity) are often linked to deep strategies and exam performance, and negative emotions (e.g., boredom and frustration) are often linked to shallow strategies and lower exam performance. In line with previous research we found the affective engagement is predictive of learning and cognitive engagement. Future research would benefit from investigating interventions meant to generate affective engagement, which could have subsequent positive impact on learning. Importantly, these inter-correlations also provide some validity evidence for the constructs measured through the ESM methodology with this sample.

Our study found that students' implementation rate varies across day of week, time of the day as well as location (see Figure 5 and 6). As discussed earlier, implementation rates indicate how well students followed their plans to engage in study events and represent students' self-regulation of learning. Our results showing students' implementation rates changes across time and location suggest that study context could be an important factor influencing students' self-regulation of learning. ESM-Mobile would be able to link the contextual information (i.e., time and location) with students' engagement. Such contextual information could also be extended to include attributions of times and locations, for example, the traffic and noise level of a location, students' class schedule for the time, etc. By linking these attribution data of study contexts, researchers would be able to investigate the interplay between study context, learning engagement, and students' self-regulation of them. This could be another opportunity for future studies.

Within ESM-Mobile, we tested two sampling methods in this study. The event-based sampling outperformed fixed sampling in many aspects, but require technological design expertise and support that often are not accessible for educational researchers. Fixed sampling offers an alternative to event-based sampling by using existing and free tools that are often available for educational researchers. The current study presented the pros and cons of these methods with empirical evidence. Future studies could consider their choice of method based upon the study needs and the resources available to the researchers. In addition, future development on the ESM-Mobile could even build data models to intelligently detect student study events and predict when student study events would occur, to improve the capturing and response rates, and reduce the fatigue effect caused by frequent surveying.

6. Limitations

There were some significant limitations to the current study. The most glaring is that we did not capture the amount of data that we had intended given that students were not often studying. As previously noted, the most common number of studying events that we captured per person was two times. Some participants even reported that the ESM reminded them that they were not studying when they should have been. This was related to the question about whether or not the method was annoying or interfering. Research with ESM tends to be done either in contained classrooms (e.g., Schmidt et al., 2015; Shumow et al., 2013; 2008) or online (e.g., Greene & Azevedo, 2010), however the current study is more ecologically valid as we are capturing students who are studying on their own time and at their own location of choice. We had a difficult time getting ample data and the data we got was very messy (as in sparse and variable), however, the trade-off is the ecologically valid nature. On the other hand, the frequent and repeated nature in ESM might have led to some degree of fatigue effect that we did not have data to address in this study. We acknowledge that ESM also could lead to test effect, especially when the ESM items are knowledge tests or performance measures. Future ESM studies should put both fatigue effect and test effect into consideration in the research design.

Other limitations were that the complexity of setting up the data collection resulted in some problems such as not collecting self-reported self-regulation at pre or post. We had two forms of the ESM so that a single form would not be too long, but the multiple forms idea was based on the expectation of capturing more study events per student. The measurement of emotions was counterbalanced across forms, but the result was simply not a lot of data for emotions since we did not get the expected number of events per participant.

In addition, using ESM in tracking students' geographic location of learning can be ethically sensitive. In our study, we were particularly careful in addressing ethical issues. For example, we specifically indicated to students in the consent forms that we were collecting their location data during their study events, and we collected students' permissions to use these data for analyses. We removed all the identifiable information from the dataset prior to analyses. We also translated the location coordinates into location categories and avoided revealing any addresses in the analyses and the reporting. Future research needs to be cautious about ethical issues in ESM studies.

7. Conclusions

We examined two approaches to using mobile technology to support experience-sampling research and believe there are several important implications for design and intervention. First, both the similarities and differences between retrospective self-report and in the moment responses should be recognized in educational research. Second, the event-based sampling has several advantages over fixed sampling (e.g., improved sampling accuracy, reduced extraneous prompts and responses, reduced missing data). The event-based sampling offered a more personalized sampling schedule yet it required programming and technical skills that are often not readily available. Third, the study identified popular study times (e.g., Mondays and nights) and locations (e.g., Home and campus buildings) for college students, and also identified times (e.g., Fridays and early mornings) and locations (e.g., work locations) where students often were not able to follow study plans. Last, the study investigated new variables (i.e., implementation rates for study time and location) that are objective data sources as new forms of evidence for self-regulation of learning and that were significantly correlated with values and emotions.

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Affordances of Using Mobile Technology to Support Experience-Sampling Method in Examining College Students' Engagement

Highlights

- Experience-sampling method collects data in the moment and the context of learning
- ESM and traditional self-reports had similar patterns but differed in details
- Event-based sampling outperformed fixed sampling in sampling accuracy
- ESM-Mobile collects data about behavioral, cognitive, and affective engagement
- Implementation rates are new forms of evidence for self-regulation of learning