2016-05-01

Measuring Student Engagement in Technology-Mediated Learning Environments

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A dissertation submitted to the faculty of
Brigham Young University
in partial fulfillment of the requirements for the degree of

Doctor of Philosophy

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May 2016

ABSTRACT

Measuring Student Engagement in Technology-Mediated Learning Environments

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This is a multiple-article format dissertation that explores methods for measuring student engagement in technology-mediated learning experiences. Student engagement is the committed, focused, and energetic involvement of students in learning. Student engagement is correlated with academic performance, student satisfaction, and persistence in learning, making it a valuable predictor of important learning outcomes. In order to identify which students need help or to evaluate how well an instructional interaction promotes student engagement, we need effective measures of student engagement. These measures should be scalable, cost effective, and minimally disruptive to learning. This dissertation examines different approaches to measure student engagement in technology-mediated learning environments that meet the identified measurement criteria. The first article is an extended literature review that examines how engagement has been measured in technology-mediated learning experiences. The second article is an instrument evaluation of an activity-level self-report measure of student engagement. The third article explores the relationships between learning management system user-activity data (log data) and results of the activity-level self-report measure of student engagement.

Keywords: student engagement, learning analytics, measurement, technology-mediated learning

ACKNOWLEDGEMENTS

I have deep gratitude for such an outstanding committee! They have truly wanted my success in this endeavor and have given great assistance through the whole process. There is a reason why all of our names are on this project! I am especially grateful to Charles Graham for providing great mentorship, encouragement, and a push or two to see this dissertation through.

This dissertation would certainly have taken two (or more) years longer if Bob Bodily hadn't been involved. I am greatly indebted to his talents of all sorts that have helped me push forward with data collection, study design, and thinking through the big challenges for this dissertation. Thanks Bob!

I am especially grateful for my wife. She chose to read books instead of watch movies these last couple of years so we could at least be in the same room together while I pushed through my projects and assignments. She is looking forward to a better social life with her husband and some new adventures.

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DESCRIPTION OF RESEARCH AGENDA AND STRUCTURE OF THE DISSERTATION

The purpose of this dissertation is to explore how to effectively measure student engagement when students learn within a technology-mediated environment. Research has found student engagement to be important to students' academic achievement, persistence, and satisfaction with learning (Finn & Owings, 2006; Fredricks, Blumenfeld, & Paris, 2004; Fredricks & McColskey, 2012; Kuh, Kinzie, Buckley, Bridges, & Hayek, 2007; Reschley & Christenson, 2012). Student engagement is especially important to the field of technology-mediated learning because of the growing use of online and blended modalities (Aud et al., 2012; Parsad & Lewis, 2008; Picciano, Seaman, Shea, & Swan, 2012; Staker, Chan, Clayton, Hernandez, Horn, & Mackey, 2011; Watson, Pape, Murin, Gemin, & Vashaw, 2014) coupled with concerning rates of student incompletion (Jordan, 2014; Patterson & McFadden, 2009; Rice, 2006; Roblyer, 2006). To keep technology-mediated learning as a useful learning option, it will be important to know how to effectively engage students and keep them engaged in technology-mediated learning.

To identify what promotes and maintains student engagement, we will need effective measures of student engagement (Oncu & Cakir, 2011). Multiple methods for measuring student engagement have been explored, including the use of physiological sensors, comments analysis of discussion board interactions, and social network analysis—though self-report methods have been the most common (Fredricks & McColskey, 2012; Henrie, Halverson, & Graham, 2015). Technology-mediated learning environments afford new avenues for measuring student engagement through data created by the technology used, such as web-cams, key strokes, and mouse movements. In this dissertation, methods for measuring student engagement in technology-mediated learning will be explored, with the goal of identifying methods that can be easily scaled and reduce disruption to learning.

Article 1 – Literature Review

We conducted a literature review to better understand what approaches have been used to measure student engagement in technology-mediated learning experiences. The results of this literature review are contained in this dissertation (Article 1 – "Measuring Student Engagement in Technology-Mediated Learning: A Review"). In this review, we found heavy use of survey methods and some use of human observation to measure student engagement. Surveys are easy to scale but disruptive to learning, and are a post hoc measure of student engagement rather than a direct measure. Human observation, on the other hand, is a direct measure of student engagement, but is difficult to scale, especially when students learn at a distance. We need measurement approaches that are both scalable and minimally disruptive, capturing student engagement as it occurs. We also found some use of physiological sensors and log data to measure student engagement. The cost and complexity of physiological sensors limits its current potential. Using log data is a much more scalable and minimally disruptive approach, but the data have not yet been shown to be a multidimensional measure of student engagement. This article was published in *Computers & Education* in September 2015 and retains all formatting, length, and style requirements of this journal. I took the lead role in this project, developing the literature review plan, coding, organization of content for the article, writing, and reviewing the writing of my co-author, Lisa. Lisa Halverson gave input, assisted with coding and writing of the article. Charles Graham provided input on the project plan and writing.

Article 2 – Instrument Validation of a Self-Report Engagement Measure

The second article in this dissertation, "Validation of a Longitudinal Activity-Level Measure of Student Engagement," discusses efforts to develop a survey instrument that measures student engagement at the activity-level. More in-the-moment research is necessary to clarify the relationship between student engagement and academic outcomes (Eccles & Wang, 2012; Fredricks & McColskey, 2012; Janosz, 2012; Sinatra, Heddy, & Lombardi, 2015). Existing measures do not directly focus on engagement in the moment (Fredricks, McColskey, Meli, Mordica, Montrosse, et al., 2011; Henrie, Halverson, & Graham, 2015). Rather, these measures attend to a student's overall experience in a class or school. Studying activity-level student engagement directly addresses the link between engagement and performance in a learning activity (Skinner & Pitzer, 2012).

We developed two short scales that measured students' cognitive and emotional engagement, and evaluated these scales using confirmatory factor analysis. These scales were cross-validated using two student samples, and were found to have good model fit. We found evidence that characteristics of the learner and the learning environment lead to unique pathways of engagement over time, which may affect the quality of achieved outcomes. Further research should better establish measurement invariance of the student engagement instrument. Further validation should compare results to other measures of student engagement or student learning. *Educational & Psychological Measurement, Journal of Psychoeducational Assessment,* or *Journal of School Psychology* are potential outlets for publishing this article. Formatting, length, and style requirements are met for inclusion in these journals. My role for this project was leading out on data collection, statistical analysis, writing of the article, and providing input on instrument development. Kristine Manwaring and Lisa Halverson developed the instrument and assisted with data collection. Ross Larsen provided advice on the statistical analysis. Charles Graham provided advice on the conception of the instrument and input on the writing of the article.

Article 3 – Exploring Log Data as a Proxy Measure of Student Engagement

The third article, "Exploring the Potential of LMS Log Data as a Proxy Measure of Student Engagement," examines the relationship between LMS log data and self-reported student engagement survey scores. Learning management systems are becoming more common in higher education courses, meaning LMS log data are an increasingly ubiquitous source of information on student involvement in learning. Computer systems are being developed that extract, analyze, and act upon these data, such as early-alert systems or intelligent tutoring systems (Bienkowski, Feng, & Means, 2012; Ferguson, 2012; Siemens, 2013). If LMS log data can act as a sufficient proxy for students' cognitive and emotional engagement, we would have a valuable source of data that is scalable and minimally disruptive to obtain. Different approaches to structure and analyze the log data are described. Log data and survey scores were correlated to understand the relationship between the two sources of data. In general, it was found that log data from the LMS did not have strong correlations with the survey data. The strength of these correlations would indicate that there is not a simple linear relationship between the amount of activity and time spent on the LMS and cognitive and emotional engagement. Reasons for this finding are discussed. *Computers & Education*, *Educational Technology Research & Development*, or *Internet and Higher Education* are potential publication outlets for this article.

Formatting, length, and style requirements are met for inclusion in these journals. I took the lead role in this project, developing and carrying out the plan for data collection, statistical analysis, and writing of the article. Robert Bodily assisted in data collection and providing input on the data collection, analysis and writing of the article. Ross Larsen provided input on statistical analysis. Charles Graham provided input on project conceptualization and writing of the article.

Article 1

Measuring Student Engagement in Technology-Mediated Learning: A Review

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Abstract

Using digital technology to deliver content, connect learners, and enable anytime, anywhere learning is increasing, but keeping students engaged in technology-mediated learning is challenging. Instructional practices that encourage greater engagement are essential if we are to effectively use digital instructional technologies. To determine the impact of innovative instructional practices on learning, we need useful measures of student engagement. These measures should be adaptable to the unique challenges to studying technology-mediated learning, such as when students learn at a distance or in a blended learning course. In this review, we examine existing approaches to measure engagement in technology-mediated learning. We identify strengths and limitations of existing measures and outline potential approaches to improve the measurement of student engagement. Our intent is to assist researchers, instructors, designers, and others in identifying effective methods to conceptualize and measure student engagement in technology-mediated learning.

Keywords: distance education and telelearning, distributed learning environments

Measuring Student Engagement in Technology-Mediated Learning: A Review

1. Introduction

Technology-mediated learning experiences are becoming the norm for today's students. Numerous one-to-one tablet and laptop initiatives are promoted by schools and governments around the world (Clark & Svanaes, 2014; Fuhrman, 2014; *Tablet initiatives*, 2014). The number of students taking online and blended courses continues to increase (Aud et al., 2012; Parsad & Lewis, 2008; Picciano, Seaman, Shea, & Swan, 2012; Staker, Chan, Clayton, Hernandez, Horn, & Mackey, 2011; Watson, Pape, Murin, Gemin, & Vashaw, 2014). Grants worth thousands and millions of dollars have been awarded by federal and private institutions for research and development of intelligent tutoring systems, digital educational games, and other systems designed to personalize instruction and engage learners (e.g., D'Mello & Graesser, 2012; Goldsworthy, Barab, & Goldsworthy, 2000; Kafai, Tynes, & Richard, 2014; *STEM Grand Challenge*, 2012; Woolf, Arroyo, Cooper, Burleson, & Muldner, 2010).

Helping students engage in learning is an important issue for research in instructional technology. High dropout rates for online courses and MOOCs continue to be a challenge (Jordan, 2014; Patterson & McFadden, 2009; Rice, 2006; Roblyer, 2006). Tools are being developed to try to identify students who may be disengaging from instruction and are thus at risk of dropping out (Bienkowski, Feng, & Means, 2013; Long & Siemens, 2011). Other researchers have studied how innovative instructional practices impact student engagement in technology-mediated experiences (e.g., Chen, Lambert, & Guidry, 2010; Junco, Heiberger, & Loken, 2011; Liang & Sedig, 2010). Determining how to best use people and technology to engage learners in meaningful and effective learning experiences is an important endeavor for researchers today.

Research that improves the design of instruction needs good measures of student engagement to evaluate the efficacy of instructional interventions. Several publications review methods and identify issues that need to be addressed to improve the measurement of student engagement (Betts, 2012; Fredricks et al., 2011; Fredricks & McColskey, 2012; Samuelsen, 2012). These publications tend to focus on self-report measures of engagement, particularly quantitative scales. But yet to be addressed are ways that student engagement can be measured in relation to the methodological issues unique to technology-mediated learning experiences. For example, observational measures implemented in classrooms where all students are present in one location would be challenging to arrange for an online course in which students learn separately and at a distance. Additionally, technology affords us with new methods to measure student engagement in ways both scalable and minimally disruptive to learning, such as using computer-generated data of user activity with a learning system (Aleven, Mclaren, Roll, & Koedinger, 2006; Baker et al., 2012; D'Mello & Graesser, 2012). The purpose of this review is to examine approaches to measuring student engagement in technology-mediated learning experiences and to identify issues needing attention to improve the measurement of engagement in such settings.

1.1 Background

Student engagement has been defined as investment or commitment (Marks, 2000; Newmann, 1992; Tinto, 1975), participation (Kuh, Kinzie, Buckley, Bridges, & Hayek, 2007), or effortful involvement in learning (Astin, 1984; Pekrun & Linnenbrink-Garcia, 2012; Reschley & Christenson, 2012; Terenzini, Pascarella, & Lorang, 1982). Researchers have used various terms to define this idea, including *student engagement, academic engagement*, *school engagement*, and *learner engagement* (Reschley & Christenson, 2012). Some would argue that each of these terms takes on different nuances in definition. For example, learner engagement could be considered a broad term that includes learning both in and outside of formal academic settings, whereas student engagement would focus solely on academic learning. We use the term student engagement, as our interest is in academic learning.

Student engagement has been studied at the level of learning within a single activity, focusing on what is happening in the moment, to the level of a student's whole school experience. Skinner and Pitzer (2012) developed a model that best explains the levels at which student engagement has been studied, as well as the general outcomes of interest at those levels. At the broadest level is institutional engagement, which focuses on activity in social institutions in general, such as school, family, and church. Outcomes of this level of engagement are character development and pro-social orientation. Moving deeper, research can focus on engagement in all school-related activities, such as involvement in clubs, sports, or other student organizations and activities as well as academic work in the classroom. The outcomes of this engagement are a sense of belonging in school and lower risks of dropout. Engagement can then be focused on involvement in a specific course, or even on a specific learning activity, the outcome being academic achievement and learning. Skinner and Pitzer's framework of student engagement is useful for identifying the purpose and scope of various measures of engagement, from factors specific to a single learning activity to broader institutional concerns. For instance, the National Survey of Student Engagement (Kuh, 2001) is best suited for studying institution-level engagement, with questions focused on learners' general experience in school. Institution-level measures would be inadequate to identify insights as to how a specific learning activity affected learner engagement in a course.

Many researchers view student engagement as a meta-construct that includes different types of engagement or other theoretical constructs, such as motivation and self-regulation (Fredricks, Blumenfeld, & Paris, 2004; Reschley & Christenson, 2012). Fredricks et al. (2004) described what have become the common sub-constructs or types of engagement: behavioral, emotional, and cognitive engagement. According to Fredricks et al. (2004), behavioral engagement includes the observable behaviors necessary to academic success, such as attendance, participation, and homework completion. Emotional engagement includes both feelings learners have about their learning experience, such as interest, frustration, or boredom, and their social connection with others at school. Cognitive engagement is the focused effort learners give to effectively understand what is being taught, including self-regulation and metacognitive behaviors (Fredricks et al., 2004). Cognitive engagement and behavioral engagement center on actions by the learner. Cognitive engagement differs from behavioral engagement because it focuses on the less observable effort expended in the mind (Appleton, Christenson, Kim, & Reschly, 2006). As student engagement includes both self-perception and behavior, self-reported and observable indicators can be appropriate.

Research has linked behavioral, cognitive, and emotional engagement to important educational outcomes, such as student persistence in learning (Berger & Milem, 1999; Fredricks et al., 2004; Kuh et al., 2008), satisfaction (Filak & Sheldon, 2008; Zimmerman & Kitsantas, 1997), and academic achievement (Fredricks et al., 2004; Hughes, Luo, Kwok, & Loyd, 2008; Kuh et al., 2007; Ladd & Dinella, 2009). Despite these findings between academic outcomes and the various engagement constructs, comparing and confirming findings from different studies is difficult (Fredricks & McCloskey, 2012, Janosz, 2012). The findings of two studies relating student engagement with positive outcomes may conflict due to differences in definition or construct conceptualization. The future success of research relating sub-constructs of engagement to specific outcomes relies on consensus of definitions and measures of engagement.

While student engagement is important in any learning context, our review focuses on student engagement in technology-mediated learning experiences: which includes any interaction of the learner with instructors, other students, or learning content through use of digital technology. This can happen face to face or at a distance, and the courses involved may be entirely online, blended, or face to face. When compared to traditional face-to-face learning experiences, these technology-mediated learning contexts pose unique measurement challenges. For example, learning that occurs at a distance is costly to observe and hard to scale. Additionally, technology-mediated learning experiences may provide meaningful student engagement data unavailable in more traditional contexts, as many of the systems used in technology-mediated learning keep records of summative and real-time data about student interactions with the system.

Fredricks et al. (2011) and Fredricks and McColskey (2012) identified methods to measure learner engagement in K-12 contexts. These methods involve surveying students or obtaining observations from teachers about student engagement. The instruments were designed not only to capture information on students' observable behaviors, such as participation or attendance, but to identify the less observable emotional, cognitive, and social experiences as well. One limitation to the measures examined in these reviews is that they were designed for, and in some cases can only be used in, face-to-face learning contexts. For example, a teacher report method would likely be ineffective for an online course for which teachers are not physically present to observe student behavior. Nor do the approaches reviewed address the challenges unique to measuring student engagement in technology-mediated learning experiences. As students learn more using technology and away from traditional brick and mortar locations, measures of engagement must be appropriate to these learning contexts. The purpose of this literature review is to explore how student engagement has been measured in technology-mediated learning experiences and to examine the strengths and limitations of those approaches.

2. Method

2.1 Overview

In this literature review, we sought to understand how student engagement has been measured in technology-mediated learning experiences. Our purpose was to learn what others have done to address challenges and opportunities unique to measuring student engagement in these contexts and to identify directions for improvement. To do so, we searched for literature on the subject from three major education and technology research databases. We then analyzed the resulting articles for the context in which student engagement was studied and the ways student engagement was defined and measured. Details of our method for conducting the literature review are described below.

2.2 Selection Procedure

We patterned our search procedure after Fredricks et al. (2011). We used three databases offered through EBSCOhost to gather literature: Education Resources Information Center (ERIC), Education Full Text, and Computers and Applied Sciences Complete (CASC). ERIC and Education Full Text were chosen for their breadth in educational research. CASC, a database with good coverage in general technology research, was chosen to find technology-related research in education that might be classified outside of ERIC and Education Full Text.

Our most important search term was *engagement*. Student engagement has become a popular term in the literature with a large research base. Although closely related terms can be found, such as *involvement*, *participation*, or *affect,* we chose to focus solely on articles using the word *engagement*. We limited results to articles with the word *engagement* in the abstract, reasoning that a study focused on research in student engagement would be represented by an abstract including that term.

In addition to the search term *engagement*, we developed three other categories of search terms to narrow results to a manageable set: *technology*, *measurement*, and *school context*. *Technology* terms, such as *computer-assisted instruction* or *online learning*, were used to identify articles related to technology-mediated learning. *Measurement* terms, like *analysis* or *instrument*, were used to narrow results to articles conducting studies that actually measured student engagement. We employed a broad definition of measurement to include both quantitative and qualitative approaches. Researchers using qualitative approaches, while not assigning numbers to determine the degree of an attribute, still conceptualized student engagement and gathered data to study the construct. *School context* terms, including *elementary education* or *undergraduate students*, were used to narrow results to academic learning experiences, the area of focus for this study, rather than publications for corporate learning or informal learning. We began with a large list of possible terms for each of these categories by reviewing those used by Fredricks et al. (2011) and exploring the thesaurus feature provided by EBSCOhost, which indexes subject terms assigned to articles by the database. Thesaurus was specifically used for developing search terms for the technology and school context categories, as terms in these categories were specifically searched for in subject fields. All possible terms were paired individually in a search with *engagement* in all three databases.

Any terms that did not yield results were dropped from the list. Final terms and search fields used in each of these categories are displayed in Table 1.

Our search began in February 2014 and concluded in December 2014. We limited results by publication type, choosing to review only scholarly journal publications. We believe this scope represents quality research publications within a reasonable breadth of the literature. Our final search resulted in a total of 407 unique articles. We then narrowed our initial collection of literature to sources truly relevant to the purposes of our study. We searched all abstracts for any indication that engagement had been measured, including phrases such as “produced higher engagement” (Neumann & Hood, 2009) or “effectively increased student engagement” (Beckem & Watkins, 2012). We also confirmed that the study was conducted in an academic context with a technology-mediated learning experience. If the abstract was unclear on any of these criteria, the article was coded as irrelevant. Following this process, we narrowed our review pool from 407 publications to 176.

2.3 Coding

Next we analyzed the remaining 176 publications to determine how research on student engagement in technology-mediated learning had been conducted. Articles were coded for relevancy and context, as well as for measures of engagement and types of engagement indicators used (see Tables 2, 3, and 4 for category definitions). We restricted relevancy to those articles in which a measurement of engagement was described and the term *engagement* was used, not a synonym of the term such as *motivation* or *interest*. For example, McNaught, Lam, and Cheng (2012) used *engagement* in their article three times but did not discuss how student engagement was measured, even though the abstract described finding a relationship between student engagement and learning outcomes. Additionally, articles were excluded if students were not using digital technology to learn. For example, Coffey (2011) noted that simulations impacted student engagement; however, when we reviewed the article we found that the study was limited to face-to-face simulation activities that did not utilize digital technologies. We excluded 63 articles from our list because they did not explicitly measure student engagement or did not study a technology-mediated learning experience.

For the research context category, articles were coded for grade level, number of participants involved in the study, type of course involved, location of the learning experience, and technology used. For the engagement measures category, articles were coded for type of measure used and level of engagement measured using Skinner and Pitzer's (2012) framework. For the engagement indicators category, researchers determined whether student engagement indicators identified by the article were behavioral, cognitive, or emotional, according to definitions taken from Fredricks et al., (2004).

Two researchers coded articles together to develop a system for coding and to establish consistency on ratings. Once a system was established, 20 percent of the articles were coded blindly by two researchers, whose coding results were then compared to determine inter-rater reliability as measured by Cohen's kappa. Three subcategories did not have a satisfactory kappa score: level of engagement (k=0.35), behavioral indicators (k=0.00), and cognitive indicators (k=0.39). These subcategories were then subject to a second review using ten additional relevant articles for which one rater identified the paragraphs that contained information about those codes and the other rated only on those paragraphs. We did this so the raters were focused more on interpreting the same evidence. Many studies did not designate engagement indicators as being behavioral, cognitive, or emotional engagement, and it was difficult to find relevant evidence in the article. Having one researcher identify the evidence first and then having both researchers code allowed them to focus on agreement of definitions rather than on agreement on locating all possible evidence. Kappa results are included in Tables 2, 3, and 4.

Coding in all categories but one yielded a satisfactory kappa score of 0.61 or higher, which Landis and Koch (1977) interpret as substantial agreement (see Tables 2, 3, and 4). The code that did not get a score of .61 or more was cognitive engagement, under the engagement indicators category. The two researchers were able to achieve .60 on this subcategory, which is considered moderate agreement. Results of indicators of cognitive engagement should be interpreted with some caution. Any coding differences were discussed by the two researchers until agreement was achieved. The remaining articles were coded by researchers separately. Trends in codes were then analyzed, with meaningful patterns reported in the results section below.

2.4 High Impact Publications

The next step of our review was to determine the impact of research measuring student engagement, which we based on citation counts from Google Scholar citation metrics as of December 2014. Google Scholar is a useful resource for gathering citation counts because of its indexing breadth and capacity to give current results (Chen, 2010; Halverson, Graham, Spring, & Drysdale, 2012). We searched the title of each relevant publication in Google Scholar and recorded the number of times the publication had been cited according to Google Scholar metrics. We sorted our results by citation count and identified a list of the ten most cited publications overall, as well the five most cited publications of the last three years (2012-2014). We then reviewed these publications to highlight the contributions made.

3. Results

In this section, we review the results of our coding and review process. We first look at trends in the contexts in which student engagement was measured, followed by an analysis of ways engagement was defined and measured. We end with a description and analysis of the high impact articles as determined by the number of citations and a review of the contributions made by these studies.

3.1 Overall Context

Much of the research we reviewed occurred in higher education contexts with undergraduate students. The largest category of research took place in face-to-face courses but focused on learning that occurred at a distance. Tables 5, 6, and 7 contain findings of the research context analysis. Studies had been conducted on a wide range of participant populations, with some studies focusing on only a small group of students in one or two courses, to large studies involving thousands and tens of thousands of students from multiple institutions (e.g., Chen et al., 2010; Chen, Gonyea, & Kuh, 2008; Han & Finkelstein, 2013). Student engagement was studied in a variety of technology-mediated learning experiences. Technology included clickers, virtual simulations such as Second Life, learning management systems, mobile applications, video lectures, and social communication technologies such as Twitter. The five most studied technologies were online discussion boards, general websites, learning management systems, general computer software, and videos.

Research we examined expressed several reasons for measuring student engagement, but by far the most prevalent was to evaluate whether a learning intervention using technology positively impacted student engagement. For example, Bolliger and Armier (2013) evaluated the impact of student-generated audio files on student engagement in a graduate-level course.

Another example includes the study done by Lehman, Kauffman, White, Horn, and Bruning (2001) on the impact of different types of instructor email content on student engagement in an online course. Student engagement was also measured to understand its relationship with other theoretical constructs in technology-mediated learning experiences, such as confidence (Barkatsas, Kasimatis, & Gialamas, 2009; Giesbers, Rienties, Tempelaar, & Gijselaers, 2014; Pierce, Stacey, & Barkatsas, 2007), self-efficacy (Mills, Herron, & Cole, 2004; Spence & Usher, 2007; Sun & Rueda, 2012), and social presence (Liu, Magjuka, Bonk, & Lee, 2007; Wise, Chang, Duffy, & Valle, 2004).

3.2 How Student Engagement Was Defined

As discussed in the introduction, student engagement has been variously defined across the research with as much divergence as agreement. We were not surprised to find great variety in the ways that student engagement was defined and operationalized in these measurements. For example, Spence and Usher (2007) focused on *courseware engagement*, which they defined as "the degree of effort and persistence students report putting forth to use each of the four primary courseware features; these are the video tutor, tutorial practice problems, guided solutions, and sample tests" (p. 273). Blackwell, Fisher, Garcia and Green (1975) were interested in *task engagement* and sought to measure student behaviors in relation to the technological tool, such as focusing eyes on device or touching the keyboard. Bluemink and Järvelä (2004) studied *joint engagement*, which they defined as intensive group work to make decisions and solve problems or tasks. Such engagement, the authors contended, "requires continuous attention to grasp the ideas of the participants and to interpret meanings" (p. 203). Other studies looked at student engagement more broadly, but broke the construct into sub-constructs, as will be discussed shortly.

Although we expected the terms to be defined and operationalized differently, we were surprised to find that most of the reviewed articles did not have clear definition statements for engagement. Student engagement was linked to motivation, participation, academic achievement, and interaction with classmates or instructors (among other factors); it was operationalized as time spent on a webpage or with eyes on a screen or as attendance in a face-to-face class. However, these were operationalizations; clear definitions were scarce. One article with a clear definition statement of engagement was by Yang (2011), who borrowed from Cole and Chan (1994, p. 259): "Students' engagement is defined as 'the extent of students' involvement and active participation in learning activities'" (p. 182). Nakamaru (2012) also clearly defined student engagement but used the words of Greene et al. (2008, p. 514): "I adopt the definition of engagement as 'the effort, both in time and energy, students commit to educationally purposeful activities'" (p. 275). Järvelä, Veermans, and Leinonen (2008) included their own working definition of engagement as "student psychological investment in learning in terms of motivational interpretations and goals as described in achievement goal theory" (p. 302). Sun and Rueda (2012) likewise had a clear and singular statement of definition: "In academic settings, engagement refers to the quality of effort students make to perform well and achieve desired outcomes" (p. 193). We found it troubling that the majority of articles reviewed included no statement expressing the researchers' definition of student engagement. If research on this topic is to gain theoretical cohesiveness, definitional clarity about engagement and its sub-constructs is critical.

When authors did not define engagement, we focused on ways they operationalized engagement, since doing so was a necessary step to measuring various indicators of engagement. Skinner, Furrer, Marchand, and Kindermann (2008) explained that the term *indicators* "refer[s] to the features that belong inside the construct of engagement proper" (p. 766), such as excitement, interest, or attention. In contrast, *facilitators* of engagement, or “the causal factors (outside of the construct) that are hypothesized to influence engagement” (p. 766), include variables such as motivation or self-efficacy. As we were interested in how engagement has been measured in technology-mediated environments, we paid close attention to how each article operationalized and measured chosen engagement indicators.

Occasionally within the same article engagement was defined in one way but operationalized and measured in another. For example, Cocea and Weibelzahl (2011) related engagement to constructs such as interest, effort, focus of attention, and motivation, and then defined it as “the entire mental activity (involving at the same time perception, attention, reasoning, volition, and emotions)" (p. 115). However, measures of engagement in this article were more narrowly behavioral, including the time spent on reading online pages and the number read, as well as the time spent, pages read, and correct/incorrect responses on online tests.

A few articles construed engagement through its opposite, by operationalizing and measuring disengagement, primarily through off-task behaviors, disruptions, or inactivity (Donovan, Green, & Hartley, 2010; Hayden, Ouyang, & Scinski, 2011; Rowe, Shores, Mott, Lester, & Carolina, 2011). Yet some research has argued that disengagement or disaffection is not merely the bipolar opposite of engagement, but its own unipolar construct (Skinner, Kindermann, & Furrer, 2009). Construct validity of student engagement can be improved through clarity of construct and sub-construct definitions.

As stated in the Methods section, we determined whether the student engagement indicators identified by the article were behavioral, cognitive, or emotional engagement indicators, as defined in Fredricks et al., (2004). We chose these categories as they are widely used; however we found a variety of other engagement sub-constructs in the literature we reviewed. For example, Dixson (2010) and Mandernach (2009) applied constructs from Handelsman, Briggs, Sullivan, and Towler's (2005) Student Course Engagement Questionnaire (SCEQ): skills engagement, emotional engagement, participation/interaction engagement, and performance engagement. Bangert-Drowns and Pyke (2002), Lim, Nonis, and Hedberg (2006), and Lim (2008) all used a seven-level taxonomy of engagement ranging from disengagement and unsystematic engagement through critical engagement and literate thinking (Bangert-Drowns & Pyke, 2001). Such examples highlight the amorphous and evolving nature of the construct and the importance of providing clear construct definitions.

Very few of the articles expressly labeled their indicators of engagement using the sub-constructs identified by Fredricks et al., (2004); even articles that discussed behavioral, cognitive, and emotional types of engagement did not identify different indictors of the sub-constructs. However, Yang (2011) not only reviewed the three sub-constructs of engagement but suggested ways to measure them broadly in computer-mediated settings and specifically linked various measurements to each category. Because Yang's development was the exception, we usually had to make subjective decisions in categorizing the indicators. Table 8 shows the range of indicators utilized to measure engagement and our categorization of them using Fredricks' et al., (2004) descriptions. We were frustrated by the lack of clarity in definitions and operationalization, which makes it difficult to understand reasons for the differences in research on student engagement.

Of the 113 articles we reviewed, 77% operationalized engagement from a behavioral perspective, with indicators that included participation, attendance, assignments completed, time logged in, and other on-task behaviors. In technology-mediated learning settings, behavioral engagement can potentially be measured by computer-recorded indicators such as assignments completed; frequency of logins to website; number and frequency of postings, responses, and views; number of podcasts, screencasts, or other website resources accessed; time spent creating a post; and time spent online.

Cognitive engagement indicators were utilized in 43.4% of the articles we reviewed (*n* = 113). Cognitive engagement, involving beliefs, values, cognitive strategy use, and planning, may not always be externally visible and may require self-reporting. Some qualitative measures attempted to gauge when cognitive processes such as reflection, interpretation, synthesis, or elaboration were shown in student-created artifacts. At times the line between cognitive and behavioral engagement became blurred. For example, Kong (2011) was interested in the effect that a cognitive tool would have on classroom dialog, but operationalized engagement using an indicator of behavior (time on task). Zhu (2006) created a detailed framework for cognitive engagement in discussion boards, but the lowest levels (a direct response, for example) overlap with behavioral engagement indicators. Clearly more work is needed to distinguish these two types of engagement and to understand how each uniquely contributes to important learning outcomes.

Emotional engagement indicators included positive or negative emotions towards learning, classmates, or instructors, as well as social interactions and a sense of community. Like cognitive engagement, emotional engagement may include self-reporting but can sometimes be seen through visible expressions of positive emotion (Bebell & Kay, 2010; Wang, 2010). Emotional engagement indicators were present in 40.7% of the 113 articles surveyed, but they were more frequently studied in the K12 context: 63.6% of K12 studies (*n* = 21) measured student engagement with emotional indicators, while only 31.3% of the higher education studies (*n* = 25) did so. We found it interesting that emotional engagement is considered important to measure at the K12 level but loses stature to researchers as students mature. Yet emotions do not cease to be critical to learning as the learner enters the university. Pekrun (2011) has argued that emotions can influence "a broad variety of cognitive processes that contribute to learning, such as perception, attention, memory, decision making, and cognitive problem solving" (p. 26). And Skinner and Pitzer (2012) made an emphatic analogy: "Emotion is likely the fuel for the kind of behavioral and cognitive engagement that leads to high-quality learning" (p. 33).

Of the 113 articles reviewed, 43 percent measured engagement along only one indicator category. However, some articles measured more than one engagement category, and more than 21% included behavioral, cognitive, and emotional indicators. Some scholars have argued that the term engagement should be used only for work including multiple components (Fredricks et al., 2004; Guthrie & Wigfield, 2000) to ensure that the richness of real human experience is understood. Thus measuring engagement across more than one indicator may produce the most productive information for researchers, instructional designers, and educators.

3.3 How Student Engagement Was Measured

Student engagement in technology-mediated learning experiences was measured in various ways, ranging from self-report surveys and interviews to assessment scores and behavior counts. Of the 113 articles we reviewed, 60.2% of the studies relied on one method of measurement, but many utilized multiple measures (39.8%). Table 9 details the types and frequency of measures used. The following sub-sections review the major methods for measuring student engagement and the types of questions that can be answered about engagement using those measures.

3.3.1 Quantitative self-report. Surveys that use quantitative items (e.g., likert scale) were commonly used for measuring student engagement in technology-mediated and blended learning (see Table 9). Some surveys contained only one or two items related to engagement, while others contained full scales with over a dozen engagement-related items. Survey items ranged from asking students how they would rate their perceived level of engagement (Gallini & Barron, 2001) to survey questions that addressed behavioral, cognitive, and emotional aspects of engagement (e.g., Chen et al., 2010; Price, Richardson, & Jelfs, 2007; Yang, 2011). Most surveys were completed by students, though some were used to collect perceptions of engagement from teachers (e.g., Gallini & Barron, 2001; Kay, 2011). Fourteen named surveys were used or adapted to measure student engagement, most of which were evaluated for their psychometric properties. Table 10 provides information about these named instruments.

The most frequently used named survey was the National Survey of Student Engagement (NSSE) developed by Indiana University (see Kuh, 2001). This institution-level survey is used to assess the quality of a students' college experience. Students are asked to report on their participation in activities shown to lead to engagement and quality educational experience, such as participation in collaborative projects, involvement in extracurricular activities, and level of preparation for class. The NSSE, often used to evaluate and compare institutions, was used in the studies we reviewed to compare the impact of different instructional interventions or modalities on student engagement. The majority of these comparisons were of face-to-face and online courses (Chen, Gonyea, & Kuh, 2008; Chen et al., 2010; Rabe-Hemp, Woollen, & Humiston, 2009; Robinson & Hullinger, 2008). One study used a portion of the NSSE to compare student engagement in classes when Twitter was used and in classes where it was not (Junco et al., 2011), while another study looked at the impact of wikis on student engagement

(Neumann & Hood, 2009). These studies highlighted engagement as a desirable outcome and examined ways instructional interventions, both large and small, impact student engagement.

Surveys are useful for investigating unobservable aspects of student engagement, particularly for understanding the emotions students experience or the mental energy or cognitive strategies they apply to learning (Appleton et al., 2006; Fredricks & McColskey, 2012). Surveys are a scalable option when students are learning at a distance, especially when compared to methods such as human observation. Surveys, however, are not always the best method for measuring student engagement. Surveys can be inappropriate for younger children, who may not understand the questions being asked. Further, timely data on student engagement are difficult to obtain via surveys. As midcourse or end-of-term self-report surveys are often lengthy, they require an inconvenient amount of time for students to complete. Moreover, the data are obtained at the end of the course or learning activity, not in the midst of it. Although this post hoc data can be used to improve future iterations of an instructional design, such data frequently have little benefit for the current students being observed. This is particularly relevant to those interested in developing systems that provide instructors and administrators feedback on student engagement in a course.

Variance in student engagement across time is also difficult to capture through surveys. Short surveys repeated periodically, such as the experience sampling method approach used to measure flow as detailed by Hektner, Schmidt, and Csíkszentmihályi (2007), is one way to capture variance in student engagement across time. However, such approaches tend to require significant effort from students completing them. Finally, surveys divert students from learning and may disrupt the very engagement we hope to measure. This problem is particularly intrusive when measuring student engagement at the activity level. More indirect measures, such as observational methods, could allow for measurement and uninterrupted learner engagement to occur simultaneously. These more indirect measures are described later in this article..

3.3.2 Qualitative measures. The second most frequent approach to measuring student engagement we observed was qualitative measures, which were used in 39.8% of the 113 studies we reviewed. These methods included direct, video, or screen capture observations of students' behavior while learning (Figg & Jamani, 2011; Bluemink & Järvelä, 2004; Rieth, Bahr, Polsgrove, Okolo, & Eckert, 1987); interviews or focus groups (Martin, Burks, & Hunt 2009; Missett, Reed, Scott, Callahan, & Slade, 2010); and analysis of discussion boards or other digital communication tools (Giesbers et al., 2014; Granberg, 2010; Sutherland, Howard, & Markauskaite, 2010), where types of behaviors and written or verbal communication were categorized using preexisting frameworks and taxonomies (e.g., Laakso, Myller, & Korhonen, 2009; Lim, 2008; Rieth et al., 1987) or by identifying themes.

Qualitative measures are particularly useful for exploratory studies characterized by uncertainty concerning how to measure or define student engagement. For example, Paulus, Horvitz, and Shi (2006) analyzed text from an asynchronous discussion board, students' written reflections, and students' responses in interviews to explore what engagement was like when graduate students learned from stories in an online environment. Rather than defining the nature of student engagement a priori to develop a survey, the authors used qualitative measures that enabled them to approach engagement inductively. One challenge with using qualitative methods, however, is that they are difficult to scale. Extensive resources may be needed to collect data. It is often necessary to analyze data manually, limiting the amount of data researchers choose to examine. Many of the studies we reviewed were able to use these methods only with small numbers of participants.

3.3.3 Quantitative observational measures. Researchers used a variety of frequency-type indicators to observe the level of students' engagement in learning. These indicators were obtained using direct human observation, video recording, and computer-generated user-activity data. Frequencies tracked included the number of posts to a discussion board (Giesbers et al., 2014; Peters, Shmerling, & Karren, 2011; Xu, 2010), time on task (Kong, 2011; Laakso et al., 2009; Lehman et al., 2001), attendance (Heafner & Friedman, 2008), assignment completion (Gleason, 2012; Madyarov, 2009; Thompson, Klass, & Fulk, 2012), number of on-task or off-task behaviors (Blackwell et al., 1975; Donovan et al., 2010; Hayden, Ouyang, & Scinski, 2011), number of edits made during a writing task or discussion board activity (Nakamaru, 2012; Wise, Speer, Marbouti, & Hsiao, 2012), or number of page views in an online resource (Cocea & Weibelzahl, 2011; Morris, Finnegan, & Wu, 2005; Steward, Stott, & Nuttall, 2011).

Observational methods, which include both frequency measures and some qualitative measures, such as discourse analysis, have the advantage of enabling researchers to measure student engagement as it occurs, rather than disrupting it or measuring it afterwards as required with surveys. Observational measures tend to focus on engagement at the activity level, which is useful for researchers interested in studying engagement within an activity or a small moment of time. While surveys can also be tailored to investigate student engagement at the activity level, observational measures tend to have the advantage of less learning disruption. Qualitative measures are effective for describing the nature of engagement, but frequency measures can be useful for tracking how a certain quality of engagement changes over time or how degrees of engagement vary among individuals or groups.

Frequency measures of student engagement may limit the aspects of engagement that can be studied. Some researchers have defined student engagement as energy in action (Russell, Ainley, & Frydenberg, 2005). Observational frequency measures, usually records of manifested behaviors, are a logical means for studying energy in action. Student engagement, however, also includes emotional and cognitive aspects. Research suggests that these other aspects of engagement have unique relationships with other learning outcomes of interest (Fredricks et al., 2004). Appleton et al., (2006) argue that the most valid measure of cognitive and emotional engagement is self-report as these aspects of engagement focus heavily on students' perceptions of their experience (see also Fredricks & McColskey, 2012). Additionally, frequency measures of behavioral engagement may not by themselves provide an adequate understanding of the quality of engagement (Appleton, Christenson, & Furlong, 2008). Henrie, Bodily, Manwaring, and Graham (2015) found that the amount of effort needed to succeed in an online class as measured by student activity in the learning management system varied from student to student, making it difficult to determine *how much* engagement is needed for quality academic performance. Careful consideration is needed to determine which measures of student engagement are most appropriate when studying the relationship between student engagement and other variables, like academic performance.

Another limitation of observational measures of student engagement is the cost required to obtain the measure. Trained observers are often used to gather data in person, which can be particularly challenging when learning occurs at a distance and with learners in varied locations. While this may be the case when human observers are required to obtain the frequency measure, using computer-recorded frequency measures presents a more scalable and cost-effective option to study student engagement. Some systems provide reports of user activity, eliminating the need for manual counting. From our review we identified 10 articles that used computer-generated data to obtain frequency measures. These data included discussion board activity, assignment submissions, pages viewed, time spent on an activity, and other types of behaviors recorded by the system. In studying student engagement in technology-mediated learning, computer or system-generated frequency data should be considered if observational measures of student engagement are desired. We were surprised that data of this type were not used in more of the studies we reviewed, as most technology systems are capable of tracking user activity. More research using computer-generated data should be done to better understand its value for studying student engagement.

3.3.4 Other methods for measuring student engagement. We tracked additional methods for measuring engagement that did not fit in the major categories of survey, qualitative methods, and frequency. Ten studies used performance as an indicator of engagement, arguing that high student performance or high completion rates provided evidence of student engagement (e.g., Liang & Sedig, 2010; Rowe et al., 2011; Schilling, 2009). Student academic performance has been shown to correlate with student engagement, and where student engagement can be used to predict performance, certainly performance could act as an indirect measure of engagement. But one must consider information that is lost when using this indirect measure. Some students may perform well but be disinterested or frustrated rather than excited, interested, and engaged. Students' positive emotional responses to learning may be important immediate outcomes to achieve, but they also affect long-term persistence (see Fredericks et al., 2004).

Another type of measure of student engagement we observed used physiological sensors, which detect students' physical responses while learning. Boucheix, Lowe, Putri, and Groff (2013) used eye-tracking technology to determine the impact of different types of animation on student engagement and learning. Shen, Wang, and Shen (2009) used skin conductance, blood pressure, and EEG sensors to measure a student's emotional engagement while learning from interactive electronic lectures. Self-report data were provided by the student while this emotional monitoring occurred. Using the self-report data, a model was trained from the physiological data to be able to predict emotional states in future data without the need of collecting self-report. The model correctly identified learning emotions 86.3% of the time.

Physiological sensors provide a potential window into students' cognitive and emotional activity. Determining emotional or cognitive states from physiological sensors, such as heart rate, may be too speculative without confirming findings with self-report data, such as what was done by Shen et al., (2009). However, if physiological data can accurately correlate with responses from self-report, then engagement can be measured without having to disrupt students from learning. The challenge with using physiological sensors is the complexity of the technology as well as the cost. The student observed by Shen et al., (2009) had to be careful about placement of sensors and was physically restricted during monitoring. However, physiological sensor technology is improving with simple and more cost-effective options, making this type of measure more feasible for studying student engagement (D'Mello & Graesser, 2012).

3.4 High Impact Analysis

Our last analysis was to determine which articles from our literature review were most frequently cited in other scholarly work. We identified the five most cited articles overall as well as the five most cited articles between 2012 and 2014. Because there was a tie for 5th place among the most cited overall, six articles are included. The references can guide researchers to publications most cited in scholarly work on student engagement in technology-mediated learning. A wide range of technology-mediated learning experiences are represented. Tables 11 and 12 identify the results of this analysis, listing bibliographic information for each article as well as total citation count.

The highest cited article overall was by Junco et al., (2011). Two college course types were studied: one that used Twitter for educational purposes and one that did not. Researchers measured students' engagement in both course types using items from the National Survey of Student Engagement. Students who took classes using Twitter were found to have a statistically significant higher degree of engagement [$F(1, 4.9) = 12.12$, $p = 0.018$]. Students from both course types had a similar level of engagement before Twitter was used.

The highest cited article since 2012 was Sun and Rueda (2012). Researchers in this study investigated the relationship of student engagement, situational interest, self-efficacy, and self-regulation for undergraduate and graduate students in blended and online courses. Researchers used an adapted version of the Engagement Scale developed by Fredricks, Blumenfeld, Friedel, and Paris (2005) that measures behavioral, cognitive, and emotional engagement. They found strong relationships between student engagement and situational interest and self-regulation. They also found that online activities may be a means of increasing students' emotional engagement.

4. Discussion

The purpose of this review was to better understand how student engagement has been measured in technology-mediated learning experiences and to evaluate the potential of these measures. Table 13 provides a summary of the strengths and limitations of the measures we reviewed. We do not feel that any particular measurement method is the best for all situations. Each approach has its own strengths and limitations that should be carefully considered by those interested in measuring student engagement in technology mediated learning.

We found that quantitative self-report, particularly surveys, was the most common measure of student engagement in technology-mediated learning experiences. Surveys are a scalable measure of student engagement. Electronic survey administration systems, such as Qualtrics, Google Forms, and Survey Monkey, make it easier to distribute surveys to students who are learning at a distance. Additionally, surveys may be the most effective means of studying the psychological and cognitive aspects of student engagement. However, surveys are not the only measurement option for studying student engagement. Observational measures can capture student engagement as it is occurring, with less interference with learning. Additionally, if student engagement is defined as applied energy (Russell et al., 2005), it makes sense to use observational techniques to obtain evidence of that applied energy.

Traditional observation measures, using human observers and coders to obtain data, can be costly to administer and to prepare observers. However, other sources of frequency data are available for studying students using technology to learn. This data comes in the form of log data, or system reports of user activity. Log data are potentially useful for measuring student engagement in technology-mediated learning (Baker et al., 2012). Systems can be designed to automatically track and report on user activity, providing ready-made frequency data. The measure is unobtrusive, capturing data behind the scenes as students learn. Systems are also capable of providing granular student engagement data at the real-time level, which may be difficult for human observers to obtain, such as the number of clicks, the speed of mouse movement, and the time activity occurred. More research is needed to better understand what log data can tell us about the cognitive and emotional experience students are having as they learn. This research will likely need to follow Shen, Wang, and Shen's (2009) example of comparing new approaches to established measures of cognitive and emotional engagement.

While we did not see as much research as we expected using log data to measure student engagement, we are aware of studies using log data to examine student learning (e.g., Arroyo, Murray, Woolf, & Beal, 2004; Gobert, Baker, & Wixon, 2015; D'Mello, Picard, & Graesser, 2007; Woolf et al., 2009). For example, Baker et al. (2012) used human observers to code students' affective states while learning with an intelligent tutoring system. Affective states observed included boredom, confusion, frustration, and engaged concentration. Data mining algorithms were then used to search for patterns in the log data from the intelligent tutoring systems that corresponded with the assessment of the human observers. The resulting models were then used to predict students' affect states from log data. These predictions were then compared to affective ratings from human observers. The prediction models were aligned with human observer ratings 70-99% of the time, depending on the affective state predicted and model used.

Other studies using log data to study student learning employed different terminology for constructs related to student engagement, such as *affect* or *involvement*. Our literature review focused only on those studies that used the term *engagement* as there was a significant amount of research to review using this term. But this review decision eliminated similar research, such as Baker et al. (2012) and others (e.g., Arroyo et al., 2004; D'Mello et al., 2007; Woolf et al., 2009). We may have also missed some studies on log data and student engagement because research in educational data mining and learning analytics is relatively new and found mostly in conference proceedings, which are generally not catalogued by the databases we used for this literature review. Future review work might look into these other sources of literature to identify trends and strengths in measures of student engagement in technology-mediated learning.

Perhaps the greatest challenge to the work of measuring and studying student engagement in technology-mediated learning, as well as the study of student engagement in general, is a lack of cohesion around definitions, models, and operationalization of student engagement. While this is expected with a relatively new construct (Fredricks & McColskey, 2012) with theoretical understanding still in development, it is difficult to identify what facilitates student engagement and how student engagement promotes other educational outcomes without clear definitions and shared measurements. This weakness is particularly challenging when studying sub-constructs of student engagement. As noted in this review and elsewhere (Reschley & Christenson, 2012), conceptual overlap of student engagement sub-construct definitions and operationalization may lead to different findings when comparing student engagement with facilitators and outcomes (Fredricks & McColskey, 2012). The lack of research on cognitive engagement and especially emotional engagement makes it difficult to determine whether it is really necessary to operationalize and define student engagement with these sub-constructs (see Janosz, 2012). Further research is essential to establish how both emotional and cognitive engagement relate to important educational outcomes and facilitators of engagement.

Student engagement can be a useful indicator of how well students are doing in achieving desirable academic and social outcomes. Monitoring student engagement could help us identify students who are on track for success and those who need additional help to persist and succeed. Measuring student engagement can provide valuable evidence for the quality of a course, learning activity, or instructional tool. Further work on developing effective measures of student engagement will increase our capacity to help students and improve instruction.

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Table 1

Search Terms

Category	Terms	Search Fields Used
Engagement	Engagement	Abstract field
Technology	“blended learning,” “computer assisted instruction,” “computer managed instruction,” “courseware,” “distance education,” “electronic learning,” “integrated learning systems,” “intelligent tutoring systems,” “online courses,” “mobile learning,” “virtual classrooms,” “web based instruction”	Subject field
Measurement	“analysis,” “assess,” “change,” “correlation,” “data analysis,” increas*, “instrument,” level*, measur*, “mixed methods research,” “questionnaire,” “regression,” “scale,” statistic*, “survey”	Title field Abstract field
School context	“elementary education,” “elementary secondary education,” “graduate students,” “graduate study,” “high school students,” “high schools,” “higher education,” “intermediate grades,” “junior high school students,” “junior high schools,” “middle school students,” “primary education,” “secondary education,” “secondary school students,” “undergraduate students,” “undergraduate study"	Subject field

Note. Term format shows whether quotes were or were not used in the search.

Table 2

Description of Research Context Coding Category

Subcategory	Kappa	Code	Description
What was the grade level of participants?	*n* = 19 ***k* = 0.867** *Po* = 0.895	K6	Participants were in kindergarten to grade 6.
		7 – 12	Participants were in 7^{th} to 12^{th} grade.
		K12	Participants included both K6 and 7-12.
		HE-U	Participants were undergraduate students at a higher education institution.
		HE-G	Participants were graduate students at a higher education institution.
		HE	Participants included both undergraduate and graduate students.
In what location did the learning experience studied take place?	*n* = 19 ***k* = 0.833** *Po* = 0.895	Face to face	Learning occurred face to face in a school classroom, computer lab, or researcher's lab.
		Distance	Learning was mediated by technology with no face-to-face interaction with other learners or with the instructor as part of the learning experience.
		Both	Learning took place both face to face and at a distance.
		?	It was unclear where learning occurred.
In what type of course did the learning experience take place?	*n* = 19 ***k* = 0.778** *Po* = 0.895	Face to face	The course met face to face in a traditional brick and mortar location.
		Online	The course was labeled an online course in the article.
		Blended	The course was labeled a blended, hybrid, or mixed method course in the article.
		?	The course type was unclear.
How many participants were involved?	---	Open coded	The article identified the number of participants, number of courses or sections, and the number of institutions involved in the study.

Note. K is Kappa score, and Po is proportion of observed agreement.

Table 3

Description of Engagement Measures Coding Category

Subcategory	Kappa	Code	Description
At what level was student engagement measured? (Based on Skinner & Pitzer, 2012)	*n* = 10 ***k* = 0.756** *Po* = 0.900	School	The measurement focused on the whole school experience, including activity both inside and outside the classroom.
		Course	The measurement focused on the whole classroom experience, including interactions of the learner with the learning content, other learners, and the instructor.
		Activity	The measurement focused on engagement in a learning activity or set of learning activities occurring within a course.
Were quantitative surveys used to measure engagement?	*n* = 19 ***k* = 1.000** *Po* = 1.000	Yes or no	Surveys with quantitative items were used, soliciting student or teacher perceptions concerning the presence or degree of particular indicators of engagement.
Were qualitative measures used to study engagement?	*n* = 19 ***k* = 0.671** *Po* = 0.842	Yes or no	Measures that assessed engagement qualitatively were used, often including interviews, open-ended survey questions, discourse analysis, or observation.
Were frequency measures used to study engagement?	*n* = 19 ***k* = 0.678** *Po* = 0.842	Yes or no	Observers obtained or kept track of frequency of behaviors, such as the number of assignments turned in or the amount of time spent on an assignment. This also included articles that obtained frequency scores for observations involving qualitative measures.
Were other measures used to study engagement? If so, describe.	*n* = 19 ***k* = 1.000** *Po* = 1.000	Yes or no	This category allowed for other categories of measures to emerge.
Was a named survey used or adapted to measure engagement? If so, what was the survey?	*n* = 19 ***k* = 0.855** *Po* = 0.947	Yes or no	The purpose of this item was to identify quality surveys used or repurposed to study student engagement.

Note. K is Kappa score, and Po is proportion of observed agreement.

Table 4

Description of Engagement Indicators Coding Category

Subcategory	Kappa	Code	Description
Did the measurement of engagement include *behavioral* indicators?	n = 10 ***k* = 1.000** *Po* = 1.000	Yes or no	"Across the various behavioral engagement scales/subscales, individual items ask students to report on their attention, attendance, time on homework, preparation for class, class participation, concentration, participation in school-based activities, effort, adherence to classroom rules, and risk behaviors" (Fredricks et al., 2004, p. 771).
Did the measurement of engagement include *cognitive* indicators?	n = 10 ***k* = 0.600** *Po* = 0.800	Yes or no	"Cognitive engagement is used as a broad umbrella term for (1) beliefs about the importance or value of schooling, learning goals, and future aspirations; (2) cognitive strategy use (how deeply students study material); (3) self-regulatory or meta-cognitive strategies (how students manage the learning processes such as planning and seeking information); and (4) doing extra work and going beyond the requirements of school. These measures of cognitive engagement incorporate aspects of motivation, self-regulated learning, and strategy use" (Fredricks et al., 2004, p. 772).
Did the measurement of engagement include *emotional* indicators?	n = 19 ***k* = 1.000** *Po* = 1.000	Yes or no	"Overall, emotional engagement scales include questions about a myriad of topics related to emotional reactions to school such as being happy or anxious; expressing interest and enjoyment; reporting fun and excitement; reacting to failure and challenge; feeling safe; having supportive or positive relationships with teachers and peers; having family support for learning; expressing feelings or belonging" (Fredricks et al., 2004, p. 772).

Note. K is Kappa score, and *Po* is proportion of observed agreement.

Table 5

Types of Courses in Which Student Engagement Was Studied

Type of Course	**Frequency**	**Percent**
Face-to-face course	54	47.8%
Online or distance course	23	20.4%
Blended course	11	9.7%
Course type uncertain	12	10.6%
Combination of courses	13	11.5%
Total	113	100%

Table 6

Level of Students Studied

Type of Course	**Frequency**	**Percent**
Grades K-6	9	8.0%
Grades 7-12	15	13.3%
Both K-6 and 7-12	9	8.0%
Undergraduate students	47	41.6%
Graduate students	14	12.4%
Both undergraduate and graduate	19	16.8%
Total	113	100%

Table 7

Location of Student Learning

Type of Course	Frequency	Percent
Face to face	39	34.5%
At a distance	47	41.6%
Both F2F and at a distance	19	16.8%
Learning location uncertain	8	7.1%
Total	113	100%

Table 8

Ways Engagement Was Operationalized

Indicator Category	Examples of How Operationalized		Example Sources
Behavioral	• Answers to recall questions • Assignments completed • Attendance in face-to-face class • Attention • Effort • Eyes on device; fingers on keyboard • Frequency of logins to website • Involvement with learning object • Number of postings, responses, & hits • Number, quality, & frequency of online posts & views • Number of podcasts used	• Off-task behaviors (inactivity, disruption, loitering too long on non-learning websites) • On-task behavior • Participation • Percentage of sessions with posting actions, views that were reads (not scans), & posts viewed at least once • Persistence • Questions asked publicly in class or online • Task engagement • Time-locked eye tracking • Time spent creating a post • Time spent online • Use or non-use of website resources, of screencasts	• Boucheix, Lowe, Putri, & Groff (2013) • Peters, Shmerling, & Karren (2011) • Thompson, Klass, & Fulk (2012)
Cognitive	• Analysis, synthesis, decision-making • Challenge • Cognitive attachment (represented by the *behavioral* indicator of on-task behavior) • Critical engagement • Elaboration • Explanation • Focus • Higher mental functions on Bloom's Revised Taxonomy	• Improved understanding • Internal dialogue • Interpretation • Literate thinking • Perceived relevance • Perceived value • Problem-solving behavior • Psychological investment in learning • Reflection • Self-regulated interest	• Bangert-Drowns & Pyke (2002) • Guertin, Zappe, & Kim (2007) • Zhu (2006)
Emotional	• Anxiety • Boredom • Cheering (that it was a "laptop day") • Collaborative social interaction • Enjoyment • Enthusiasm • Excitement • Fun	• Happiness • Interest • Passion • Sense of class community • Student-student interactions • Visible expressions of pleasure • Expressed desire to use the tool again	• Kay (2011) • Missett, Reed, Scot, Callahan, & Slade (2010) • Sun & Rueda (2012)

Table 9

Distribution of Engagement Measures Used

Measures	Description	Frequency
Quantitative self-report	Surveys, scales, or questionnaires with quantitative items soliciting student or teacher perceptions of the presence or degree of particular indicators of engagement	61.1%
Qualitative measures	Measures that assessed engagement qualitatively, often through interviews, open-ended survey questions, discourse analysis, or observation	39.8%
Quantitative observational measures	Frequency of behaviors observed or monitored, including number of assignments turned in or amount of time spent on an assignment, as well as frequency scores for observations obtained through qualitative measures	34.5%
Other	Other methods used to measure engagement, including performance and bio-physiological sensors reported as alternative methods to measure engagement	11.5%

Table 10

Named Surveys Used to Measure Student Engagement

Name of instrument	**Authored by**	**Internal consistency (Cronbach's Alpha)**	**Methods used to assess construct validity**	**Types of indicators (B=behavioral C=cognitive E=emotional)**
Academic Engagement Form	Richardson, Long, & Foster, 2004	0.56 – 0.70	Principal components analysis and factor analysis	B C E
Classroom Survey of Student Engagement	Ouimet & Smallwood, 2005	---	---	B C E
Classroom Engagement Survey	Unpublished survey from Hamilton, 2005	---	---	C E
Engagement Scale	Fredricks, Blumenfeld, Friedel, & Paris, 2005	0.67 – 0.86	Exploratory factor analysis	B C E
Learning Object Evaluation Scale	Kay & Knaack, 2007, 2009	0.63 – 0.89	Principal components factor analysis	C E
Mathematics & Technology Attitude Scale	Pierce, Stacey, & Barkatsas, 2007	0.65 – 0.92	Principal components and exploratory factor analysis	B C E
National Survey of Student Engagement	Indiana University; Kuh, 2001	0.84 – 0.90	Principal components analysis	B C E
Online Student Engagement Scale	Dixson, 2010	0.91	Exploratory factor analysis	B C E
Perceived Interest Questionnaire	Schraw, 1997	0.92	Principal factor analysis	E
Positive and Negative Affect Schedule	Watson, Clark, & Tellegen, 1988	0.84 – 0.90	Principal factor analysis	E
Presence Questionnaire	Witmer & Singer, 1998	0.88	Cluster analysis	B
Short Flow State and Core Flow State Scales	Jackson & Eklund, 2004	0.80	Confirmatory factor analysis	B C E
Student Assessment of Learning Gains	Lim, Hosack, & Vogt, 2012	0.69 – 0.96	---	---
Student Course Engagement Questionnaire	Handelsman, Briggs, Sullivan, & Towler, 2005	0.76 – 0.82	Exploratory factor analysis	B C E
Student Engagement Questionnaire	Coates, 2006	0.59 – 0.81	Congeneric measurement modeling	B C E
Virtual Course Flow Measure	Shin, 2006	0.63 – 0.88	Principal components analysis	B

Table 11

Top Five High Impact Articles as Determined by Total Citation Counts as of December 2014

# of Citations	**Authors**	**Title**	**Journal**
406	Junco et al., 2011	The Effect of Twitter on College Student Engagement and Grades.	*Journal of Computer Assisted Learning*
193	Conrad, 2010	Engagement, Excitement, Anxiety, and Fear: Learners' Experiences of Starting an Online Course	*The American Journal of Distance Education*
160	Zhu, 2006	Interaction and Cognitive Engagement: An Analysis of Four Asynchronous Online Discussions	*Instructional Science*
145	Lim, Nonis, & Hedberg, 2006	Gaming in a 3D Multiuser Virtual Environment: Engaging Students in Science lessons	*British Journal of Educational Technology*
140	Chen et al., 2010	Engaging Online Learners: The Impact of Web-Based Learning Technology on College Student Engagement	*Computers & Education*
140	Bebell & Kay, 2010	One to One Computing: A Summary of the Quantitative Results from the Berkshire Wireless Learning Initiative	*The Journal of Technology, Learning, and Assessment*

Table 12

Top Five High Impact Articles as Determined by Total Citation Counts Over Years 2012-2014

# of Citations	Authors	Title	Journal
37	Sun & Rueda, 2012	Situational Interest, Computer Self-Efficacy and Self-Regulation: Their Impact on Student Engagement in Distance Education	*British Journal of Educational Technology*
30	Blasco-Arcas, Buil, Hernández-Ortega, & Sese, 2013	Using Clickers in Class. The Role of Interactivity, Active Collaborative Learning and Engagement in Learning Performance	*Computers & Education*
18	Owston, York, & Murtha, 2013	Student Perceptions and Achievement in a University Blended Learning Strategic Initiative	*The Internet & Higher Education*
14	Wise et al., 2012	Broadening the Notion of Participation in Online Discussions: Examining Patterns in Learners' Online Listening Behaviors	*Instructional Science*
12	Han & Finkelstein, 2013	Understanding the Effects of Professors' Pedagogical Development with Clicker Assessment and Feedback Technologies and the Impact on Students' Engagement and Learning in Higher Education	*Computers & Education*

Table 13

Summary of Strengths and Limitations of Engagement Measures

Measure	Strengths	Limitations
Quantitative self-report	• Easy to distribute • Usable in F2F and distance learning • Useful for self-perception and other less observable engagement indicators • Effective for studies of student engagement at the course and institution levels	• May be too difficult for young children to complete • May be tedious if frequent repeated measures are necessary • Cannot be used to observe engagement in action unobtrusively
Qualitative measures	• Useful for exploratory studies of student engagement • Can be applied to less observable aspects with self-report • Can enable data gathering without disrupting learning • Effective for studies of student engagement at the activity level	• Costly and challenging to train human observers • Difficult to scale • Difficult to do when students learn at a distance
Quantitative observational measures	• Appropriate measure when defining engagement as energy in action • Effective for studies of student engagement at the activity level • Abundant data through systems • Less disruption to learning during data gathering	• May not adequately measure cognitive and emotional engagement • Costly, challenging, and difficult to scale if human observers gather data
Physiological sensors	• Effective for studies of student engagement at the activity level • Possible to use existing technologies to obtain data (i.e., webcams and track pads) • Potential approach to measuring cognitive and emotional engagement	• Difficult to scale because of cost • Needs further research to determine type of engagement information that can be obtained • Requires specialized training to use instruments and interpret data

Article 2

Validation of a Longitudinal Activity-Level Measure of Student Engagement

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Abstract

This study reports on the development of a multidimensional, activity-level student engagement instrument. More activity-level research is necessary to clarify the fuzzy relationship between student engagement and academic outcomes. Existing measures do not directly focus on engagement "in-the-moment." Rather, these measures attend to a student's overall experience in a class or school. Studying activity-level student engagement directly addresses the link between engagement and performance in a learning activity. Using confirmatory factor analysis, we evaluated two short scales that measured students' emotional and cognitive engagement. These scales were cross-validated across two student samples with good model fit. We found evidence that characteristics of the learner and the learning activity lead to unique pathways of engagement over time, which may affect the quality of achieved outcomes. Further research should better establish measurement invariance of the student engagement instrument. Further validation should compare results to other measures of student engagement or student learning.

Validation of a Longitudinal Activity-Level Measure of Student Engagement

Introduction

Student engagement, defined as invested, concentrated, and energetic involvement in learning, is commonly seen as essential to academic success. Student engagement has been found to correlate with students' persistence in learning (Berger & Milem, 1999; Kuh, Cruse, Shupe, et al., 2008), student satisfaction (Filak & Sheldon, 2008; Zimmerman & Kitsantas, 1997), and academic achievement (Hughes, Luo, Kwok, & Loyd, 2008; Kuh, Kinzie, Buckley, Bridges, & Hayek, 2007; Ladd & Dinella, 2009). As high dropout rates, student indifference, and growing dissatisfaction with academic performance draw greater attention from educators, researchers, policy makers, employers and parents (Hammond, Linton, & Smink et al. 2007; Duncan, 2013), knowing what effectively engages students in learning is essential.

To study the relationship between interventions and student engagement, we need effective measures. Research suggests that to understand the link between student engagement and learning outcomes, student engagement must be studied using a fine-grained approach, examining a student's learning experience closer to real-time and over more than one point in time (Eccles & Wang, 2012; Fredricks & McColskey, 2012; Sinatra, Heddy, & Lombardi, 2015). While student engagement is conceived as a state, malleable and impacted by context (Fredricks, Blumenfeld, & Paris, 2004; Furlong & Christenson, 2008; Skinner & Pitzer, 2012), it is often measured using one-time assessments of students' general engagement in a course or school (Fredricks, et al., 2011; Henrie, Halverson, & Graham, 2015). This approach neglects the change in student engagement from day to day depending on students' academic progress, the nature of the learning activity, and other contextual factors. An intensive longitudinal approach to studying student engagement at the level of learning would better capture this ebb and flow.

The experience sampling method (ESM), developed by Larson and Csikszentmihalyi, is a popular approach to intensive longitudinal research (see Csikszentmihalyi & Larson, 1987; Hektner, Schmidt, & Csikszentmihalyi, 2007; Kubey, Larson, & Csikszentmihalyi, 1996). The method involves regularly signaling study participants to complete a short survey throughout the day over a short period of time. This approach has been successfully used in educational research to study student engagement (see Park, Halloway, Arendtsz, Bempechat, & Li, 2012; Shernoff & Schmidt, 2007; Shernoff, Csikszentmihalyi, Schneider, & Shernoff, 2003). One limitation to the experience sampling method survey is that it uses a general conceptualization of student engagement. Most research on student engagement supports a multidimensional conceptualization, with several unique factors, such as cognitive or emotional factors (Fredricks et al., 2004; Reschly & Christenson, 2012). If our measurement instruments are better aligned with existing theory, we will more capably contribute to an understanding of student engagement in learning. The purpose of this study is to validate an experience sampling instrument designed to capture a multidimensional, activity-level conceptualization of student engagement.

Russell, Ainley, and Frydenberg (2005) describe student engagement as “energy in action” (p. 1). This energy is manifest not only in the physical involvement in school activities, but as internal cognitive and emotional processes taking place as students learn. Student engagement is best seen as a malleable state (Fredricks, Blumenfeld, & Paris, 2004), impacted by characteristics of the learner, including their motivation to learn (Russell, Ainley, & Frydenberg, 2005; Skinner & Pitzer, 2012), and their previous knowledge and skill. Engagement is also impacted by characteristics of the learning experience, including the design of the learning activity or relationships with peers and the instructor (Biggs, Kember, & Leung, 2001). The nature and degree of engagement in learning leads to various academic and social outcomes, including student achievement, persistence, satisfaction, and belonging (Fredricks et al., 2004; Skinner & Pitzer, 2012). This transactional approach of defining engagement has also been described by others (see Biggs, Kember, & Leung, 2001; Eccles & Wang, 2012; Lawson & Lawson, 2014). Figure 1 depicts our transactional model of student engagement.

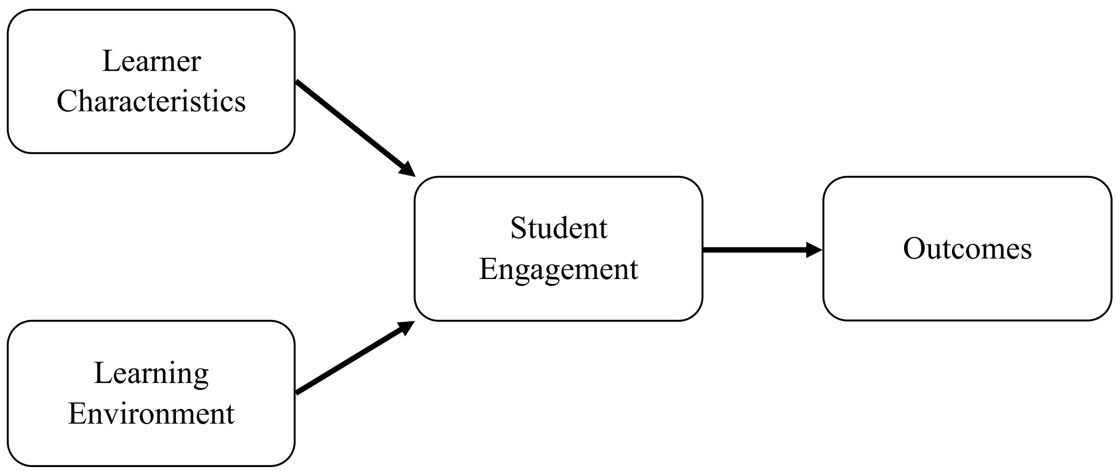

Figure 1. Transactional model of student engagement.

Student engagement has been theorized to comprise different factors, including behavioral, cognitive, emotional, social, academic, psychological, and agentic factors (Appleton, Christenson, Kim, & Reschly, 2006; Finn & Zimmer, 2012; Fredricks, et al., 2004; Reeve & Tseng, 2011; Reschly & Christenson, 2012). While there is considerable overlap among proposed factors, there are also unique variations in student engagement definitions. The lack of consensus around definitions and operationalization of student engagement is a major challenge to student engagement research (Janosz, 2012; Reschly & Christenson, 2012; Sinatra et al., 2015). This lack of consensus can lead to conflicting relationships between student engagement and other measured outcomes (Fredricks & McColskey, 2012; Shernoff & Schmidt, 2007).

Varying definitions likely exist as different audiences care about student engagement for different reasons. Some are interested in engagement from a dropout perspective, while others are interested in engagement because of interest in achieved learning outcomes. Skinner and Pitzer (2012) developed a framework that attempts to organize different approaches and foci of engagement. The framework outlines contexts with varying degrees of scope, each contextual level having specific outcomes of interest and different approaches of defining engagement. At the broadest level is engagement in social institutions, such as in family, church or school. Outcomes of interest at this level of engagement are pro-social orientation and character development. Moving deeper is engagement at the school level, which includes engagement in all school-related activities, including sports, clubs, and other student organizations and activities as well as engagement in academic work. Outcomes of engagement at this level include a sense of belonging in school and a lower risk of dropout. The next layer is engagement in a specific course, or even a specific learning activity, with the outcome being academic achievement and learning.

Our interest is on student engagement at the learning activity level, as engagement at this level directly relates to the achievement of learning outcomes. Many school and course-level survey instruments exist for measuring student engagement, but little has been done to develop activity-level instruments (Fredricks et al., 2011; Fredricks & McCoslkey, 2012; Henrie, Halverson, & Graham, 2015). These course-level instruments contain items such as "How interested are you in your Math course material?" (Ouimet & Smallwood, 2005, p. 15), "Adults at my school listen to the students" (Appleton et al., 2006, p. 436), or "I check my schoolwork for mistakes" (Fredricks, Blumenfeld, Friedel, & Paris, 2005, p. 319). These types of items have students respond to a general, accumulated experience in class or at a school. The phenomena measured by these types of items may not always occur in the moment or have relevance to a specific learning activity. Furthermore, course or school-level items would be inadequate to identify insights into how a specific learning activity affected student engagement, or how one's engagement in a specific assignment led to achievement on that assignment. It is therefore important to appropriately operationalize the construct of student engagement at the activity level. Such an operationalization would include indicators of engagement that occur in the moment and would be common across different types of learning activities.

Our proposed instrument focuses on students' cognitive and emotional engagement in learning. While many engagement factors could be studied, cognitive and emotional engagement have an established theoretical and empirical research base from which to build (see Fredricks et al., 2004). We define cognitive engagement as *the mental energy students apply to learning*. At the activity level, cognitive engagement would be characterized as attention, concentration, curiosity and absorption in learning. Emotional engagement is *the positive emotional response students have to learning*. These emotions are expressed at the activity level as enjoyment, excitement, and interest during a specific learning activity. The presence of cognitive engagement is indicative of an *effort* to learn, while the presence of emotional engagement implies the potential *willingness* to learn. We believe the synergy of cognitive and emotional engagement can lead to the greatest level of learning gains (see also Fredricks et al., 2011). As students' cognitive and emotional engagement cannot be directly observed, a self-report instrument is necessary to study these constructs (Appleton, et al., 2006). Our efforts to develop a multidimensional, activity-level measure of student engagement are described below.

Method

Participants

Participants in this study were undergraduate students from two western United States universities. All were students in courses delivered in a blended learning format, with subjects ranging from general education courses in humanities, history, and composition, to upper-level undergraduate courses in nursing, web development, and educational technology. Nine instructors over a combined 14 sections were involved in the study. Of the student sample, 319 indicated a willingness to participate in the study. While the majority of the students in each class chose to participate in the study, a small number did not, which may bias the results. Study participants were predominantly female (74.5%) between the ages of 21 and 25 (77.6%). The majority race among our samples from both universities was Caucasian. A monetary compensation was provided to students for their participation in the study.

Data Collection

A longitudinal activity-level survey of student engagement was designed for this repeated-measure study (see Appendix). The survey was designed to be short, similar to other experience sampling method instruments, so as to be used effectively for intensive longitudinal research. Seven items were used to measure students' cognitive and emotional engagement. Four items used a five-point Likert scale, with questions asking students to rate their engagement experience from "not at all" to "very much." The remaining three items used a seven-point semantic differential response scale, with the positive end indicating an aspect of engagement and the negative end indicating disengagement. A list of survey items is included in Table 1. We took the experience sampling method survey from Hektner, Schmidt, and Csikszentmihalyi (2007; see also Csikszentmihalyi & Larson, 1987), and expanded it to include both emotional and cognitive engagement items. Additional items came from a review of several popular course-level student engagement surveys (Fredricks, Blumefeld, Friedel, & Paris, 2005; Skinner, Kindermann, & Furrer, 2009), Skinner and Pitzer's (2012) work on engagement and disaffection, and a literature review of student engagement (Fredricks, Blumenfeld, & Paris, 2004). Questions were devised to best capture in-the-moment engagement states and activity. For example, the item "How well were you concentrating" would likely be present more often in the moment than the item "I checked my homework for mistakes."

Table 1

Origin of Student Engagement Survey Items

	Original ESM Item (Hektner, Schmidt, & Csikszentmihalyi, 2007).	Fredricks et al., 2004 (Review)	Fredricks et al., 2005 (Survey)	Skinner et al., 2008; Skinner & Pitzer, 2012
Did you enjoy this activity?	X	X		X
Was this activity interesting?	X	X	X	X
Excited to Bored (Reversed)	X	X	X	X
Did you wish you had been doing something else? (Reversed)	X			
How well were you concentrating?	X	X		X
Passive to Active	X	X	X	X
Focused to Distracted (Reversed)		X	X	X

Participating students self-selected for involvement in one of two groups: Group 1 (n = 241) received three surveys to complete over the course of the semester, and Group 2 (n = 78) received two surveys each week to complete during the course of the semester. Specific learning activities were chosen by researchers from each class and participants were asked to respond about their experience with the chosen learning activity. A variety of learning activities were selected in order to capture a range of experiences in which students might be engaged in learning, including lectures, discussion boards, quizzes, online videos, class projects, reading assignments, and essays. In addition to surveys, grades for the assignments associated with the engagement surveys were obtained. Research indicates that a positive relationship between student engagement and grades should be expected (Fredricks et al., 2011; Skinner & Pitzer, 2012). Final course grades were obtained at the end of the semester. We also collected learner characteristic data at the beginning of the semester through a survey, including information about students' self-regulation, self-efficacy, and interest in the course in addition to gender and age (see Appendix; items adapted from Biggs, Kember, & Leung, 2001; Pintrich, Smith, Garcia, & McKeachie, 1993).

Data Analysis

Confirmatory factor analysis was used to analyze the factor structure of the student engagement instrument items using the Mplus 7.3 statistical software package. Since the same participants were used across several time points, as would be done in a longitudinal study, the confirmatory factor analysis was done together with multilevel modeling to account for dependence in the data, with specific time points represented in level one, nested within specific participants at level two. The model was developed using data from Group 1, then cross validated on the data obtained from Group 2. The change in engagement over time for Group 1 was analyzed using multilevel modeling to determine whether there was a significant slope and whether any existing change was linear. Finally, to confirm and analyze the relationship between engagement and performance for Group 1, assignment grades were regressed on cognitive and emotional engagement for their respective time points. Figure 2 depicts the model for a single time point.

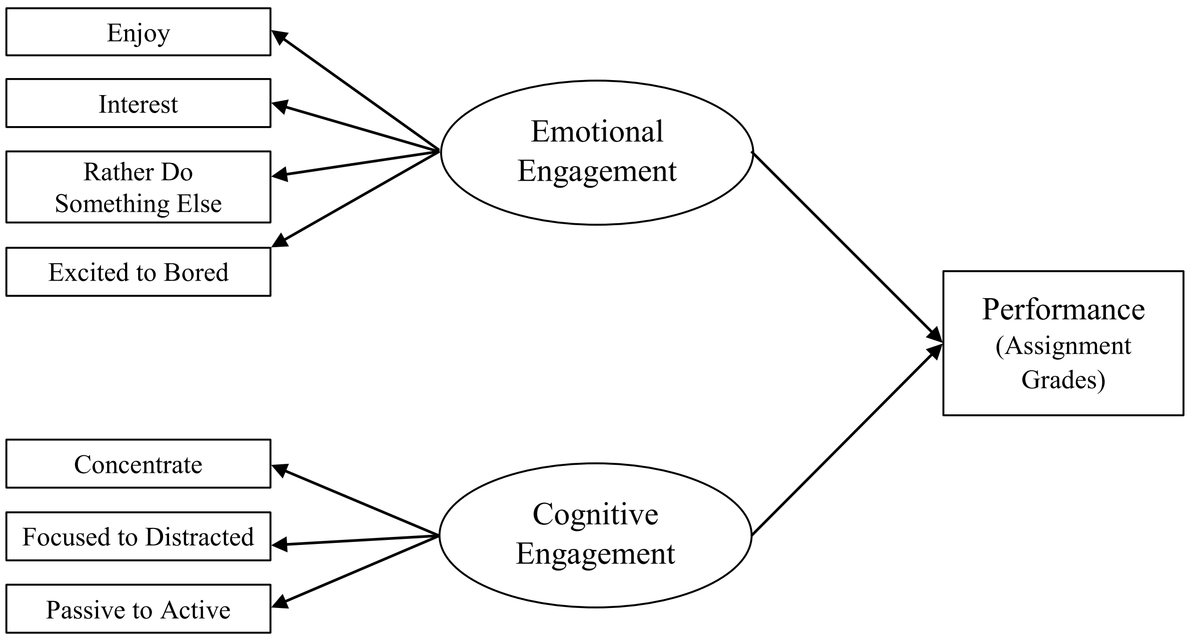

Figure 2. Model of student engagement within a single time point.

Results

Missing Data

The survey response rate varied for both groups (see Table 2). Group 1, comprised of 241 participants, completed engagement surveys at three separate time points. The highest response rate was at time point 1 (48.5%), and the lowest was at time point 2 (36.5%). One hundred and twelve students (46.5%) did not complete any surveys across the three time points. This response rate is similar to Shernoff and Schmidt's (2007) study that used the experience sampling method. In Group 2, participants were surveyed 23 times across eleven consecutive weeks during the semester. A total of 1400 surveys were collected for a response completion of 88%.

Table 2

Engagement Survey Response Rate for Group 1

	Survey 1	Survey 2	Survey 3
Response Rate	n=117 48.5%	n=88 36.5%	n=102 42.3%

Note. Total sample size was 241.

We analyzed the patterns of missing survey data to determine whether the data were missing completely at random (MCAR; the probability of having missing data is unrelated to the value of the measured variable or any other measured variable), missing at random (MAR; the probability of having missing data is unrelated to the value of the measured variable but is correlated with other measured variables), or missing not at random (MNAR; the probability of missing data is related to the value of the measured variable). Mplus has several techniques for estimating missing data that are MCAR or MAR. Missing survey data were found to be correlated with grades in the course. It is likely that students who dropped out of or were failing class may have been disinterested in study participation. We would therefore classify these missing data as missing at random.

Furthermore, eight students had missing data on grades (see Table 3 for descriptive statistics for grades). These students were confirmed to have dropped the class before the end of the semester, which removed their performance history from the course. Having missing grade data was uncorrelated with any of the other measured variables. Students could have been missing on grade data for several reasons, such as random illness, being over-scheduled, or other personal circumstances. As these factors could not be accounted for, and missing grade data were not related to any other measured variable, we determined the grade data were missing completely at random. Missing grade and student engagement data were estimated using Maximum Likelihood Robust (MLR) estimation on Mplus, with final grades and learner characteristic information to inform the missingness for survey data, and learner characteristic survey information to inform the missingness for grade data.

Table 3

Descriptive Statistics for Grades

	N	Min.	Max.	Mean	Std. Deviation	Skewness		Kurtosis	
							Std. Error		Std. Error
Final Grade	311	.027	1.000	.918	.128	-3.606	.138	16.950	.276
Grade-Time 1	311	.000	1.000	.905	.230	-3.298	.138	10.072	.276
Grade-Time 2	311	.000	1.000	.895	.245	-2.912	.138	7.623	.276
Grade-Time 3	311	.000	1.000	.904	.225	-3.237	.138	10.095	.276
Valid N (listwise)	311								

Checking Multilevel Modeling Assumptions

In checking for multilevel modeling assumptions, we found that there were some outliers in grades, as some students did not complete assignments or had dropped out of the course. We determined to run analysis with both outliers included and excluded to better understand the impact of outliers. Other than grades, no other univariate outliers were detected. While most of the continuous data had normal distributions (for example, see Figure 3), grades did not. There was a strong negative skew and a potential ceiling effect in grades (see Table 3). We believe this warranted an investigation into the differences in results when using censoring in Mplus. We analyzed the distribution of results from a Mahalanobis test and found no major gaps to indicate multivariate outliers. A review of the scatterplot comparing the standardized residuals to the standardized predicted values did not reveal any concerns with linearity, though it did confirm a ceiling affect with grades (see Figures 4 and 5).

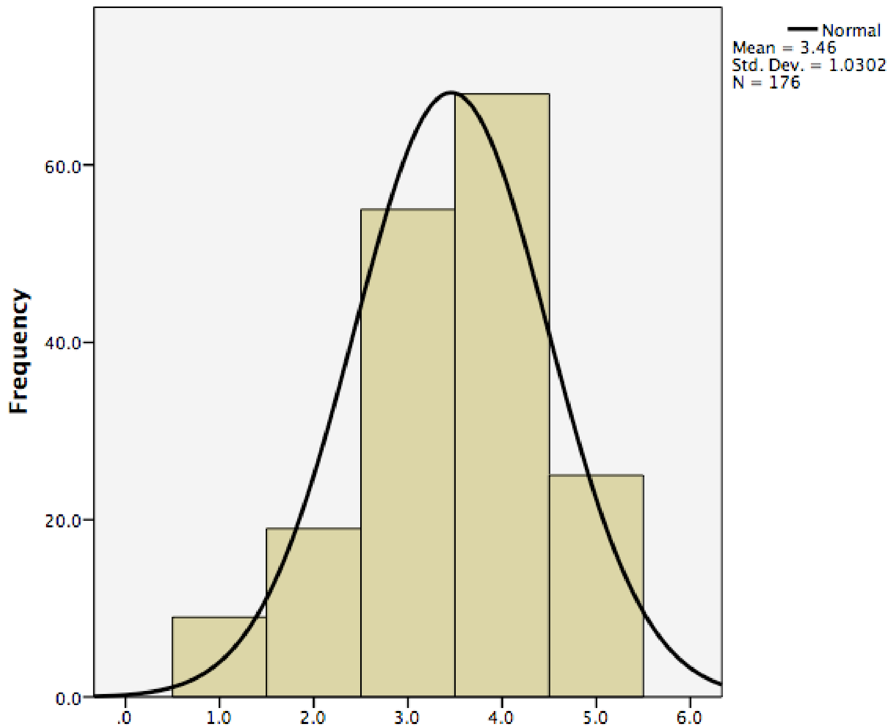

Figure 3. Distribution of interest indicator at time point 1.

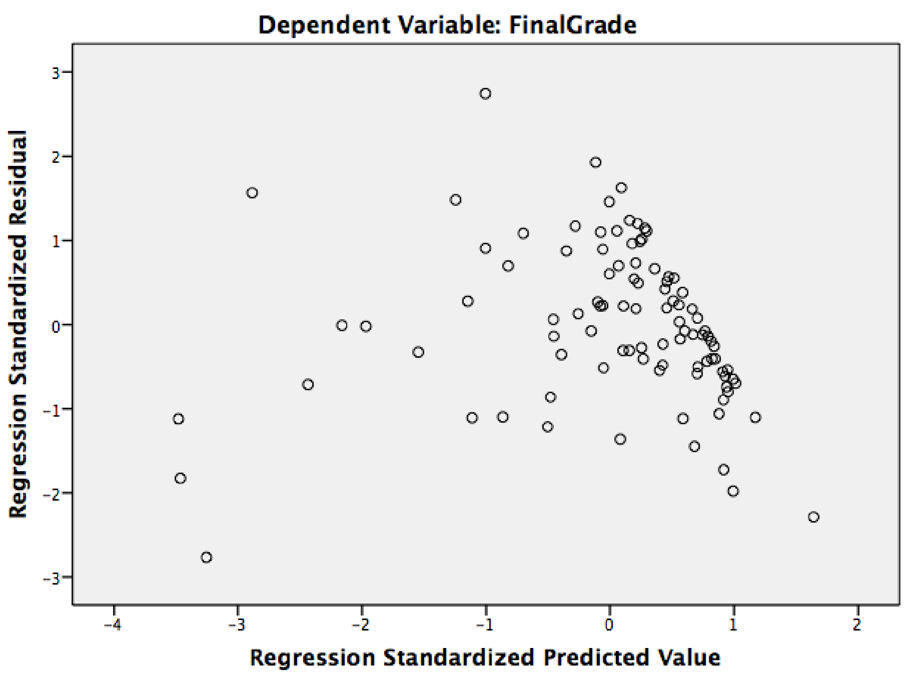

Figure 4. Scatterplot comparing standardized residuals to standardized predicted values.

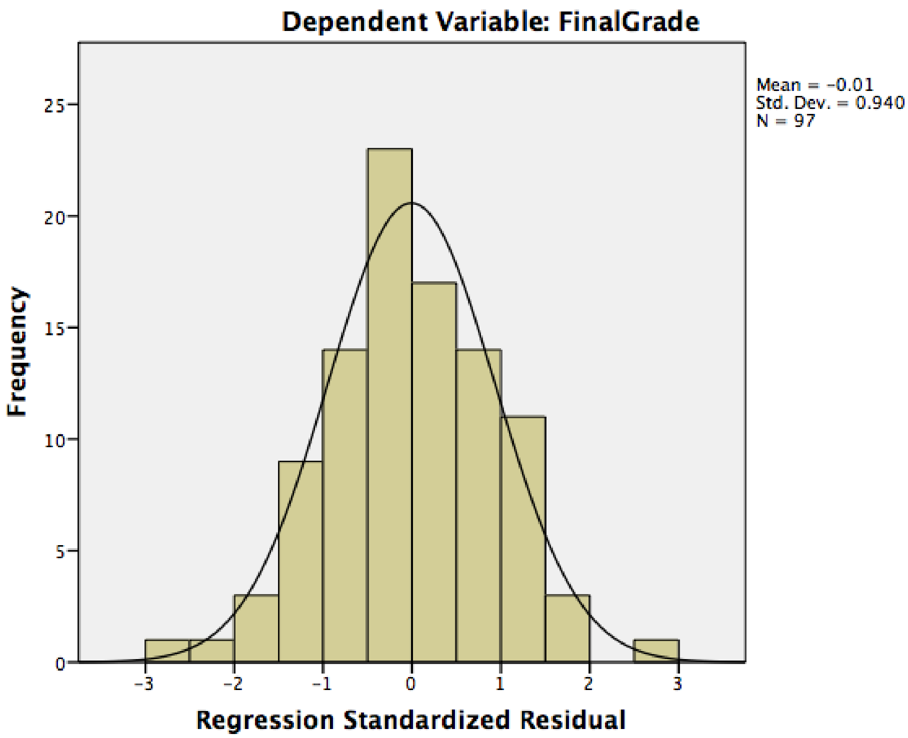

Figure 5. Histogram of standardized residuals.

We investigated multiple levels of clustering by assessing the design effect, which examines the impact of the clustering level on the standard errors (see Muthen & Satorra, 1995). We began with the lowest level of clusters after individuals, which would be specific courses. Above that, we could also cluster by type of course (i.e., mastery-based or traditional, general education courses or upper-level undergraduate courses). The design effect sizes for course were high enough that we could not safely ignore clustering at that level (DEFF > 2).

We chose to develop the model using data from participants from Group 1 as this group generally had the highest number of participants completing surveys. Initial confirmatory factor analyses that included all 241 students from Group 1, using MLR to estimate missing data, revealed that data from participants who had not completed any surveys were estimated to be the mean. As a result, there was a large number of students with engagement scores at the mean (see Figure 6). Doing multiple imputations to estimate missing data would not converge. It was

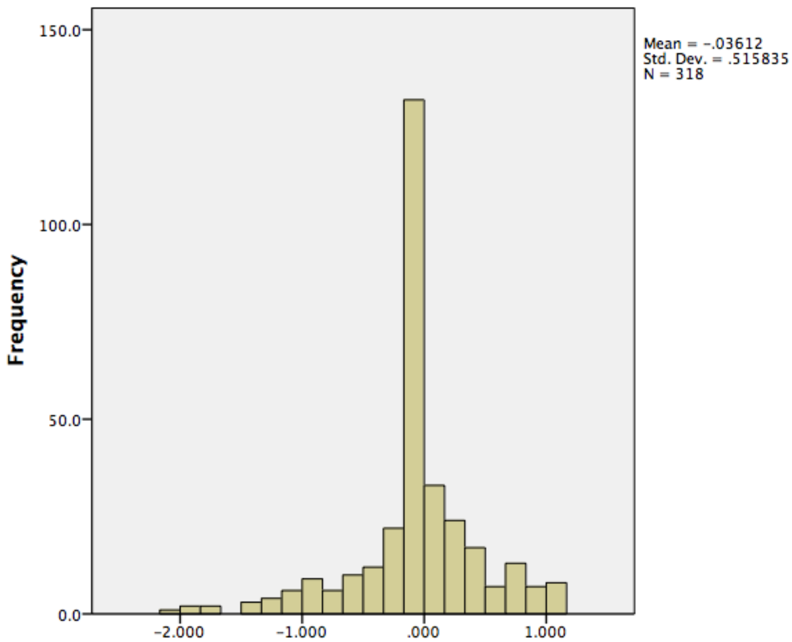

Figure 6. Cognitive engagement at time point 1 with all participants.

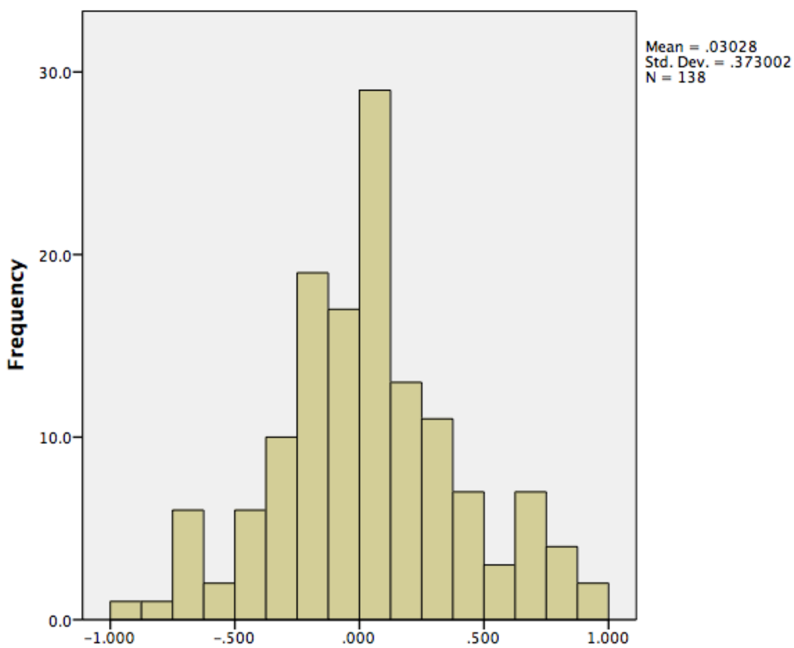

Figure 7. Cognitive engagement at time point 1 with missing on all surveys removed.

determined that the 112 students missing on all surveys biased results and were therefore excluded from the analysis. With students missing on all surveys removed from the data, the distribution of student engagement was more normal (see Figure 7).

Confirmatory Factor Analysis

Overall, the emotional and cognitive engagement factors were represented well by the hypothesized indicators. Correlated errors were found between concentration and focus as well as enjoyment and interest, indicating that factors unaccounted for in the model influenced the variance between these two pairs of indicators beyond the factors accounted for in the model. As the two pairs of factors were similar to each other, the errors were permitted to be correlated in the model. The adjusted model had good model fit (RMSEA = 0.050, CFI = 0.985, TLI = 0.971, SRMR = 0.033). Using Cronbach's alpha, emotional engagement had a scale reliability of 0.81 – 0.85 across the three surveyed time points, while cognitive engagement had a scale reliability of 0.64 – 0.80. The reliability of the cognitive engagement scale varied much more than emotional engagement, but the alpha scores were considered acceptable.

Table 4 contains descriptive statistics and factor loadings of the student engagement indicators and Table 5 describes the descriptive statistics of the student engagement factors. The emotional engagement factor was able to explain more variance among the emotional engagement indicators than did the cognitive engagement factor. The concentration indicator was the weakest of all the indicators, though concentration was statistically significant to the model, as were all the other engagement indicators. Additionally, emotional engagement had a wider distribution than cognitive engagement and had more variance. This would indicate that student's had a wider range of emotional responses to their learning experience, while cognitive engagement was more static.

Table 4

Descriptive Statistics and Factor Loadings of Cognitive and Emotional Engagement Indicators

	Min/ Max	Mean	St. Dev	Unst. Factor Loading	St. Factor Loading	St. Error	Sig	R^2
Cognitive Engagement								
How well were you concentrating?	1/5	3.83	0.90	1.00	1.80	0.00	NA	0.30***
Passive to Active	1/7	4.64	1.59	2.19	6.98	0.33	$p < 0.001$	0.47***
Focused to Distracted (Reversed)	1/7	5.15	1.79	1.50	4.74	0.21	$p < 0.001$	0.43***
Emotional Engagement								
Did you enjoy this activity?	1/5	3.36	0.96	1.00	1.33	0.00	NA	0.57***
Was this activity interesting?	1/5	3.56	0.90	0.99	1.24	0.08	$p < 0.001$	0.61***
Did you wish you had been doing something else? (Reversed)	1/5	2.96	1.12	1.18	1.83	0.09	$p < 0.001$	0.56***
Excited to Bored (Reversed)	1/7	4.30	1.31	1.33	2.42	.13	$p < 0.001$	0.53***

Note. n = 414. *** Significant at < 0.001 level.

Table 5

Engagement Factor Descriptive Statistics

	Min.	Max.	Mean	Std. Deviation
Cognitive Engagement	-1.53	0.94	0.01	0.50
Emotional Engagement	-2.10	1.50	0.01	0.72

The correlation between cognitive and emotional engagement was surprisingly high ($r = 0.823$, $p < 0.001$). We attempted to include the higher-order factor of student engagement in the model, however this model would not converge. The high correlation between the two factors would indicate that a higher-order factor would exist. Convergence issues may be due to having a small sample size. The difference in variance and distribution between cognitive and emotional engagement suggests that the two factors behave uniquely, despite the strong correlation. These differences are also manifest in the change over time, as will be reported in a section further below.

Cross Validation

The student engagement model established using the data from group 1 was cross-validated using the data from participants in group 2. Using the data from group 2, the student engagement model was also found to have good model fit (RMSEA = 0.071, CFI = 0.963, TLI = 0.929, SRMR = 0.027). An analysis of measurement invariance was conducted to confirm that the scales from the two groups were comparable in both factor loadings and estimated intercepts. This is done by analyzing the difference in the chi-square and degrees of freedom between the configural and weak measurement invariance models and again between the weak and strong measurement invariance models using the Satorra-Bentler Scaled Chi-Square Difference Test. The differences were statistically significant for weak measurement invariance ($TRd = 13.99$, $\Delta df = 5$, $p = 0.016$). This means that the scales between the two groups are not exactly comparable. Once again, this may be an issue due to sample size, but it could also be related to the differences in how the two groups completed student engagement surveys. Group 1 only completed 3 student engagement surveys over the semester, while Group 2 completed two each week. Group 2 may have developed a unique approach to completing engagement surveys over time as they had frequent use of the survey.

Analysis of Change Over Time

The change in emotional and cognitive engagement across time was studied to determine whether any change existed and whether that change was linear. Table 6 shows the results of that analysis. Cognitive engagement did not have a statistically significant change over time.

The change in emotional engagement over time was statistically significant, curvilinear in shape, concave down, with an overall decline in emotional engagement over time. Assignment grades were not found to have a statistically significant change over time. Figure 8 depicts the average mean of grades over time and Figure 9 depicts the average mean of emotional and cognitive engagement over time.

Table 6

Change in Student Engagement Across Time

	B	Variance
Cognitive engagement		
Slope	-0.007	0.002
Quadratic	-0.015	0.000
Emotional engagement		
Slope	0.242	0.001
Quadratic	-0.173*	0.000

Note. * Significant at <.05 level.

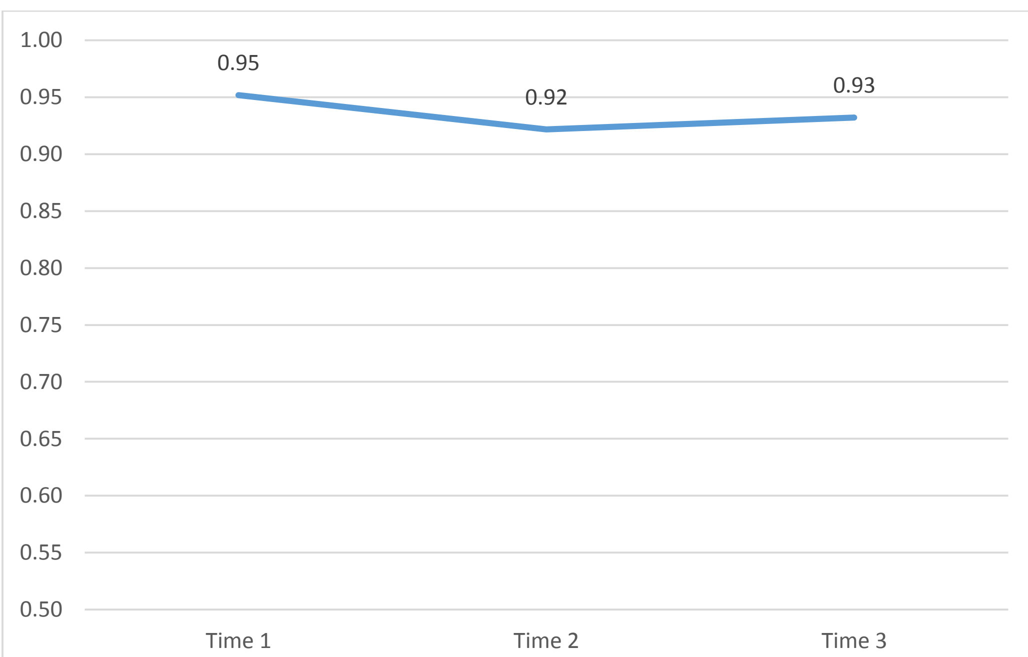

Figure 8. Change in average assignment grades over time.

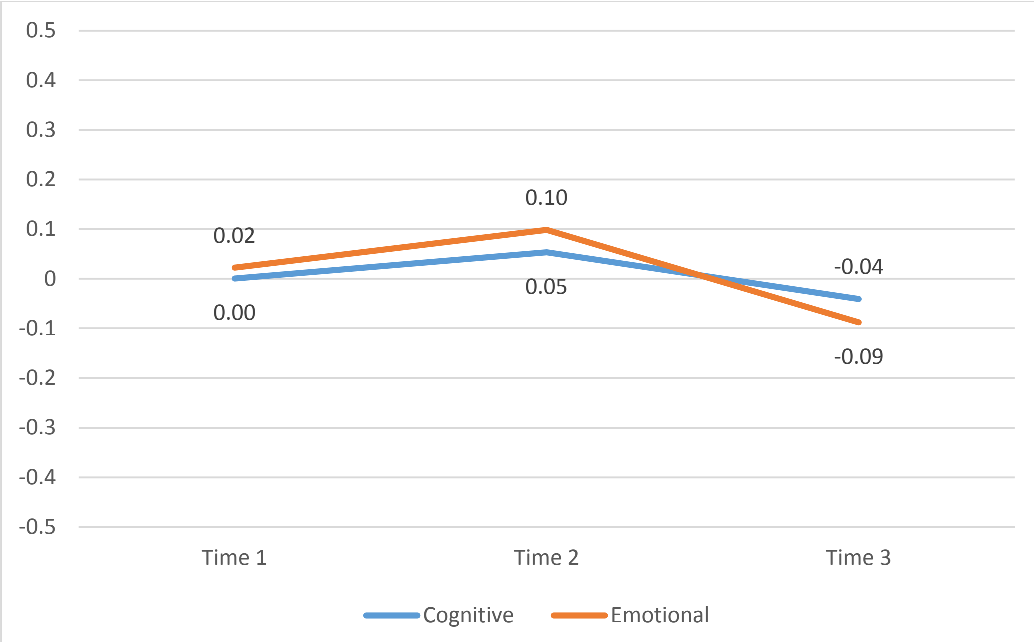

Figure 9. Change in average emotional engagement and cognitive engagement over time.

We did an initial investigation into how learner characteristics and the learning activity impact student engagement. We were unable to achieve convergence when looking at the impact of learner characteristic and learning activity variables on student engagement through structural equation modeling, but we did explore differences in student engagement graphically. Figures 10 and 11 depict change in emotional engagement over time broken down by the course one was involved in or the initial level of personal interest in the subject matter of the course. Similar results were found with cognitive engagement. These findings indicate the potential impact learner characteristics and course design can have on student's engagement.

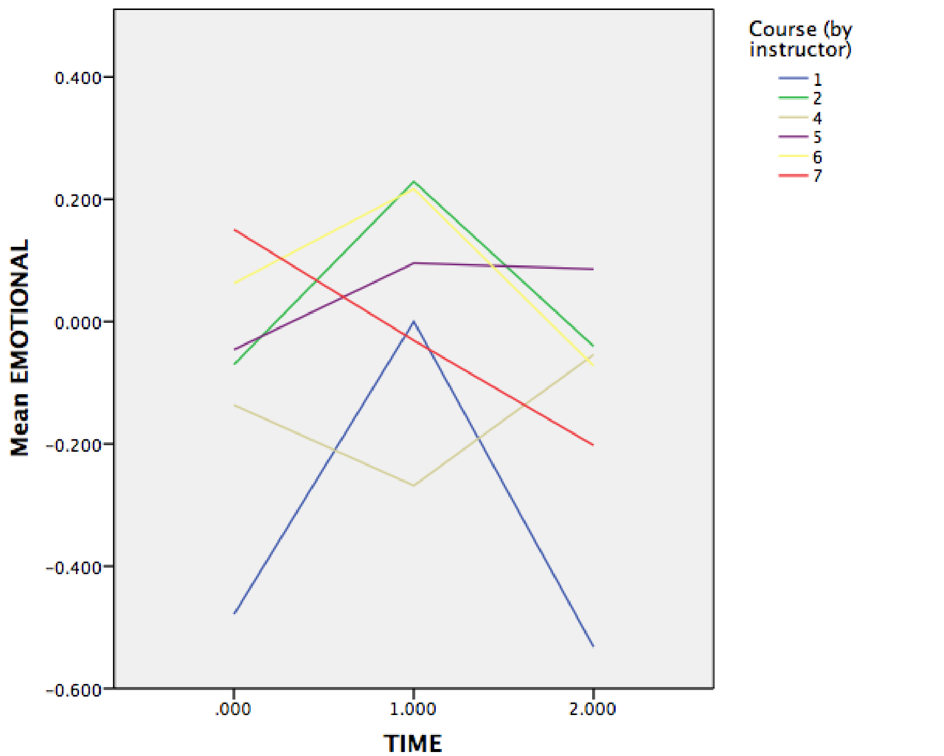

Figure 10. Change in average emotional engagement over time by course.

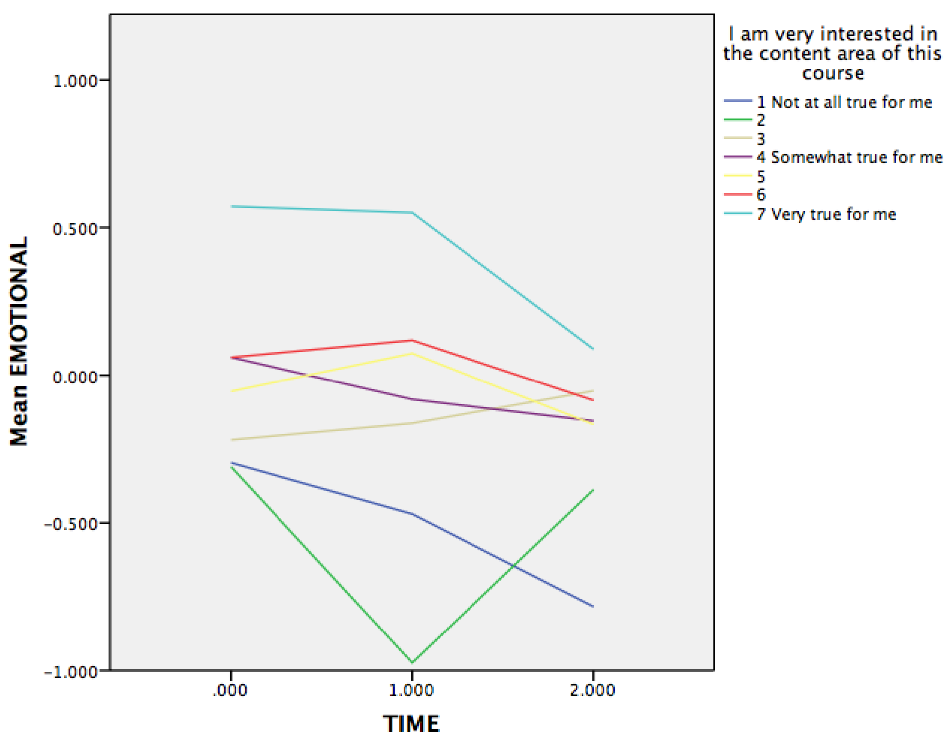

Figure 11. Change in average emotional engagement over time by personal interest in course subject.

Regression of Assignment Grades on Student Engagement

Cognitive and emotional engagement were regressed on assignment grades using multilevel modeling. No statistically significant relationship between student engagement and grades was found. This makes some sense as there was very little variance in assignment grades. The change in cognitive and emotional engagement was also regressed on the change of grades. This analysis would not converge. This, again, may be a sample size issue; more likely it is related to the little variance in assignment grades for this sample of students. Table 7 shows the correlations between the main variables of this study.

Table 7

Correlations of Grades and Engagement Factors

	Assignment Grade	Emotional Engagement	Cognitive Engagement
Assignment Grade	1.000		
Emotional Engagement	0.091	1.000	
Cognitive Engagement	0.083	0.823*	1.000

Note. * Correlation significant at the $p < 0.001$ level.

Discussion

The purpose of this study was to develop a measure of student engagement that was both activity-level and multidimensional in scope. We found good fit for a model that included both cognitive and emotional engagement scales. This model evidenced configural measurement invariance when analyzed in a separate data set. This model, however, was not confirmed to have weak or strong measurement invariance. While confirming weak and strong measurement invariance is desirable, we have not seen other studies that developed student engagement surveys use this level of rigor for cross-validation. At the minimum, we have established similar model structures between the two groups as has been done in the other studies. Future student engagement scale development studies should seek to establish weak and strong measurement invariance when conducting cross-validation to ensure that the student engagement scales are similar both in factor loadings and intercepts. Obtaining a sufficient sample size would be important to this future work. Our findings are also limited by our response rate. Many students in the courses we studied did not complete engagement surveys (sometimes as much as 64% of non participation). Future work should try to ensure a broad sample of students to produce more generalizable results, or conduct further investigation into which students are not completing surveys and reasons for non-participation.

We were surprised at the lack of a relationship between activity-level student engagement and grades as previous research had confirmed this relationship (see Fredricks et al., 2011; Skinner & Pitzer, 2012). We believe this finding highlights the importance of Janosz's (2012) call to better investigate and establish the relationship between engagement and important academic outcomes. Other studies have found significant relationships between student engagement and grades (see Fredricks et al., 2011). The instruments used in those studies were course or institutional-level surveys. Perhaps engagement in a specific activity does not have much bearing on performance in a class or even within the single activity. It is also possible that the grades we obtained were not an adequate measure of learning, and that a relationship between student engagement and performance would be found if another measure of learning was used. Or perhaps the assignments and courses we reviewed did not require a substantial degree of engagement to perform well. Even if this were the case, we would still believe that engagement in learning is important in school, even if it is not significantly related to assignment grades or final grade. Other important outcomes of interest would include persistence or learning retention. For example, we may have two students, one who is interested in the course and one who is not. Both successfully pass the course, but the interested student is able to retain what was learned longer than the disinterested student. Relationships between engagement and outcomes such as these are important to explore and would better substantiate the perceived importance of student engagement in learning.

Finally, we found evidence in our analysis of the impact characteristics of the learner and the learning activity can have on student engagement. Not only was engagement not stable over time, but the change in engagement was impacted by course factors and learner characteristics. Looking at the average of engagement across time and across all courses showed little change in student engagement over time. However, when looking at specific groups of students, such as students in the same course or students with a certain learner characteristic, we found varying pathways of engagement over time. Our limited sample size did not permit us to adequately investigate these factors at the course level, but the averages we did obtain suggest the importance of further investigation of the impact of learner and course factors on student engagement pathways over time. When these factors are accounted for in statistical analysis, we may be better able to explain the relationship between engagement in learning and other outcomes of interest, such as grades. This is an area of inquiry that is important for future research on student engagement.

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Appendix

Emotional Engagement Scale

1. Did you enjoy this activity? Not at all 1 2 3 4 5 Very Much
2. Was this activity interesting? Not at all 1 2 3 4 5 Very Much
3. Did you wish you had been doing something else? Not at all 1 2 3 4 5 Very Much
4. Describe your mood during this activity: Excited 1 2 3 (Neither 4) 5 6 7 Bored

Cognitive Engagement Scale

1. How well were you concentrating? Not at all 1 2 3 4 5 Very Much
2. Describe your mood during this activity: Passive 1 2 3 (Neither 4) 5 6 7 Active
3. Describe your mood during this activity: Focused 1 2 3 (Neither 4) 5 6 7 Distracted

Learner Characteristics Survey

Questions 1 – 14: 1 Not at all true for me; 2; 3; 4 Somewhat true for me; 5; 6; 7 Very true for me

1. I believe I will receive an excellent grade in this class.
2. I'm confident I can understand the most complex material in this course.
3. I'm confident I can do an excellent job on the assignments and tests in this course.
4. Considering the difficulty of this course, the teacher, and my skills, I think I will do well in this class.
5. I often feel so lazy or bored when I study for my classes that I quit before I finish what I planned to do.
6. I work hard to do well in my classes even if I don't like what we are doing.
7. When course work is difficult, I give up or only study the easy parts.
8. I like the subject matter of this course.
9. I am very interested in the content area of this course.

10. Even when course materials are dull and uninteresting, I manage to keep working until I finish.
11. Understanding the subject matter of this course is very important to me.
12. I am capable of solving, or getting help to solve, my computer-related problems.
13. I am very comfortable doing class work that is online.
14. I am capable of using the internet to find information I need.

Questions 15 – 22: 1 Never or only rarely true for me; 2 Sometimes true of me; 3 True of me about half the time; 4 Frequently true of me; 5 Always or almost always true of me

15. My aim is to pass the course while doing as little work as possible.
16. I only study seriously what's given out in class or in the course outlines.
17. I find I can get by in most tests by memorizing key sections rather than trying to understand them.
18. I see no point in learning material which is not likely to be in the examination.
19. I often spend extra time trying to obtain more information about class topics.
20. I test myself on important topics until I understand them completely.
21. I come to most classes with questions in mind that I want answering.
22. I make a point of looking at most of the suggested readings that go with lectures.
23. Are you male or female? (Male; Female)
24. What is your age? (18-20; 21-23; 24-26; 27-30; 31-35; 36-40; 41-45; 46+)
25. What is your estimated cumulative GPA? (<2.5; 2.6-3.0; 3.1-3.5; 3.6-4.0; First semester of college (No GPA))
26. What year are you in school? (Freshman; Sophomore; Junior; Senior)
27. Have either of your parents completed a four-year college/university degree? (Yes; No)

28. How many hours a week do you work for pay? (0 hours; 1-10 hours; 11-20 hours; 21-30 hours; 30+ hours)
29. Before this semester, had you ever taken an online course? (Yes; No)
30. Before this semester, had you ever taken a hybrid/blended course? (A course where some of the class time is replaced with on-line or technology based learning activities.) (Yes; No)
31. Do you prefer to learn online, F2F, or does it not matter? (Online; Face-to-face; Doesn't matter)

Article 3

Exploring the Potential of LMS Log Data as a Proxy Measure of Student Engagement

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Abstract

This study examines the relationship between LMS log data and self-reported student engagement survey scores. Learning management systems are becoming more common in higher education courses, meaning LMS log data are an increasingly ubiquitous source of information on student engagement in learning. Computer systems are being developed that extract, analyze, and act upon these data, such as early-alert systems and intelligent tutoring systems. Should log data serve as a meaningful proxy for survey scores, these data would be a minimally disruptive and scalable approach to quickly identify who needs help, evaluate design, and personalize instruction. We investigate multiple approaches to structuring the log data, such as using one week's worth of log data compared to one day's worth of log data, as well as aggregating log data at differing levels of granularity. The log data variables defined by these alternative structuring approaches were correlated to the student engagement survey scores to study the relationship between these two sources of data. This analysis was done for data from three separate courses. Statistically significant, but small, correlations were found in one course ($r = 0.23 - 0.33$). Overall, log data were not found to be a strong proxy measure for students' self-reported cognitive and emotional engagement. Our results underscore the complexity of learning and the relationship between observed and reported cognitive and emotional states. Future educational research using log data will need to account for the complex factors that help explain trends in student engagement.

Exploring the Potential of LMS Log Data as a Proxy Measure of Student Engagement

Introduction

Student engagement—the focused, committed, energetic involvement in learning—is commonly seen as an essential element to academic success (Sinatra, Heddy, & Lombardi, 2015). Research has shown that student engagement is significantly related to important educational outcomes, such as achievement, persistence, and completion (Finn & Owings, 2006; Fredricks, Blumenfeld, & Paris, 2004; Fredricks & McColskey, 2012; Kuh, Kinzie, Buckley, Bridges, & Hayek, 2007; Reschley & Christenson, 2012), making student engagement a valuable predictor of academic success.

While student engagement is important to any learning experience, it is particularly relevant to the field of technology-mediated learning. The number of students taking online and blended courses is on the rise (Aud, Hussar, Johnson, Kena, Roth et al., 2012; Parsad & Lewis, 2008; Picciano, Seaman, Shea, & Swan, 2012; Staker, Chan, Clayton, Hernandez, Horn, & Mackey, 2011; Watson, Pape, Murin, Gemin, & Vashaw, 2014). Watson et al. (2014) report that in the 2013-2014 school year, 30 states had fully online K12 schools, with over 300,000 students attending. Furthermore, eleven states have laws permitting students to choose to take online courses from a range of providers in place of face-to-face courses. As adoption increases, a growing concern is the high incompletion rates for online instruction (Jordan, 2014; Patterson & McFadden, 2009; Rice, 2006; Roblyer, 2006). Knowing what leads to disengagement or what promotes and maintains engagement in technology-mediated learning is necessary to maintain technology-mediated learning as a viable learning option (Dixson, 2010).

A key component to establishing a knowledge-base of what promotes student engagement in learning is informative measures of student engagement (Hollands & Bakir, 2015;

Oncu & Cakir, 2011; Sinatra, Heddy, & Lombardi, 2015). Research is ongoing in developing measures that can assist in identifying disengaging students or how an instructional intervention impacts student engagement. Self-report methods are common though other methods are still being explored (Fredricks & McColskey, 2012; Henrie, Halverson, & Graham, 2015). Measures of student engagement that will be most useful to identifying and helping at-risk students and to assess and improve technology-mediated instruction will be minimally disruptive, scalable, and measure engagement at the activity level. The purpose of this article is to explore a source of data that has the potential to meet these measurement criteria: user activity log data produced from learning management systems (LMS).

Defining Student Engagement

There are many unique conceptualizations of student engagement. While general conceptualizations exist, many theorists argue for a multidimensional definition of student engagement. The literature describes academic, behavioral, emotional, affective, psychological, social, cognitive, and agentic dimensions (Finn & Zimmer, 2012; Fredricks et al., 2004; Henrie, Halverson, & Graham, 2015; Reeve & Tseng, 2011; Reschley & Christenson, 2012; Sinatra, Heddy, & Lombardi, 2015). Our work focuses on student's cognitive and emotional engagement. While a variety of engagement factors exist, cognitive and emotional engagement have an established empirical research and theoretical base that supports the importance of these two constructs to learning (see Fredricks, Paris, & Blumenfeld, 2004, Halverson & Graham, 2015). Cognitive engagement is *the mental energy students apply to learning*, including attention, concentration, curiosity and absorption in learning. We define emotional engagement as *the positive emotional response students have to learning*, such as enjoyment, excitement, and interest. Cognitive engagement implies an *effort* to learn, while emotional engagement indicates a potential *willingness* to learn. This synergy between cognitive and emotional engagement can lead to the greatest level of learning gains (see also Fredricks et al., 2011), making both of these factors an important consideration for measurement.

Activity-level

Student engagement has been studied at the level of learning within a single activity, focusing on what is happening in the moment, to the level of a student's whole school experience. Skinner and Pitzer (2012) developed a model that explains the levels at which student engagement has been studied, as well as the general outcomes of interest at those levels. At the top-most level is institutional engagement, which focuses on activity in social institutions in general, such as school, family, and church. Outcomes of this level of engagement are character development and pro-social orientation. The subsequent level is engagement in all school-related activities, such as clubs, sports, or other student organizations and activities as well as academic work in the classroom. The outcomes of this engagement are a sense of belonging in school and lower risks of dropout. The most granular level is engagement in a specific course, or even on a specific learning activity, the outcome being academic achievement and learning.

Skinner and Pitzer's framework of student engagement is useful for identifying the purpose and scope of various measures of engagement, from factors specific to a single learning activity to broader institutional concerns. For instance, the National Survey of Student Engagement (Kuh, 2001) is best suited for studying institution-level engagement, with questions focused on learners' general experience in school. Institution-level measures would be inadequate to identify insights as to how a specific learning activity affected learner engagement in a course (Janosz, 2012; Lawson & Lawson, 2013). Wang, Bergin, and Bergin (2014) stated, "Engagement should be measured at the same specificity level as the intervention and as other key variables" (p. 518). Our interest is on student learning, persistence through a course, and the impact of instructional design on student engagement. The most appropriate level of engagement for this focus would be the activity level, where measures focus on students' engagement in specific learning activities.

Minimally Disruptive

Russell, Ainley, and Frydenberg (2005) have described student engagement as "energy in action," a description also applied by other researchers (see Appleton, Christenson, Kim, & Reschley, 2006; Halverson & Graham, 2015; Skinner & Pitzer, 2012). Some measures of student engagement are better at capturing energy in action than others. Some can measure student engagement as it happens, while others must disrupt engagement or wait until the episode of engagement has completed in order to obtain the measure. Perhaps the most disruptive measure of student engagement is self-report, which requires that students' turn their focus from learning to focus on participating in a survey or interview (see Gobert, Baker, & Wixon, 2015). However, Appleton et al., (2006), argue that the most valid measure of cognitive and emotional engagement is self-report as these aspects of engagement focus heavily on students' perceptions of their experience (see also Fredricks & McColskey, 2012). Current work is exploring other approaches to measure the cognitive and emotional dimensions of student engagement, such as using physiological sensors (see D'Mello & Graesser, 2012; Shen, Wang, & Shen, 2009). This work is innovative, but can be complicated and costly to use. Future measurement development work should focus on providing valid measures of student engagement that minimize disruption to learning.

Scalable

The capability of expansive use of a measure, particularly for quantitative analysis, is an important feature. Some measures are more scalable than others. Observational techniques, which employ human observers that record information such as behavior, facial expression, and dialogue, are an example of a measure that is difficult to scale. It can be costly to train and use observers. It is also difficult to obtain good inter-rater reliability (Gobert, Baker, & Wixon, 2015). Greater issues arise for using observational techniques when learners are engaged in learning at a distance. Rather than using an observer for a group of students in one location, like a classroom or computer lab, observers would have to be scattered across the range of locations where learners may be learning, observing single learners or small groups of learners, depending on the activity. Surveys, on the other hand, are more scalable. Their cost is minimal, and they can be distributed electronically, enabling simple distribution in classrooms or in homes so long as there is Internet access.

Potential of Log Data

One possible approach to measuring student engagement that more effectively strikes a balance between being an activity-level measure that is both minimally disruptive and scalable is using the log data from learning systems as a measure. Log data are a record of a user's activity within a system. Log data may include click or page view counts, time spent on a given action, keyboard strokes, results of an activity (such as performance on a quiz), and counts of any other activity that may occur within a system. Log data have potential as a measure of student engagement. Log data are an *activity-level* measure, detailing real-time changes in user interactions with the system. Log data are a *minimally disruptive* source of data, as they are automatically tracked behind the scenes. Log data can also be *scalable*: learning software and online programs can be designed to be used by millions of users. Despite these strengths, further work is needed to understand the value and meaning of system log data.

The use of learning management systems (LMS) to deliver learning content, facilitate faculty and student interaction, and track performance is becoming ubiquitous. Log data from these systems are often available for extraction from the LMS provider, making it a potential source of activity-level data to study student learning. Previous research has explored the value of LMS log data (Beer, Clark, & Jones, 2010; Cocea & Weibelzahl, 2011; Macfadyen & Dawson, 2010; Morris, Finnegan, & Wu, 2005). Much of that attention has focused on the relationship between log data and performance. Recent work, however, has investigated the relationship between log data and other outcomes. For example, Henrie, Bodily, Manwaring, and Graham (2015) analyzed the relationship between student's self-reported satisfaction with learning and log data from the LMS. They found that students who spent more time and had more page views during a learning activity were often less satisfied with their learning experience, indicating potential frustration, confusion, or boredom. Baker, et al. (2012) had observers code the affective states of students as they learned on an intelligent tutoring system. They then used data mining algorithms to develop prediction models that used log data from the tutoring system to predict the affective states coded by the observers. These models were able to predict observed affective states with a 77% to 99% accuracy on new data. This type of work has been replicated elsewhere (D'Mello & Graesser, 2011; Pardos, Baker, Pedro, Gowda, & Gowda, 2013).

Park (2015) argued that more research is needed to investigate how log data from the LMS relates to other outcomes such as student engagement. His work has captured both log data from the LMS and student's self report data on their cognitive and emotional engagement, and examined what can be learned from having both types of data. What has not yet been done is an investigation of how the log data from the LMS relate to students' cognitive and emotional engagement. This work is needed in order to verify that log data could be used as a meaningful measure of student engagement.

Students' log data are an indicator of their involvement in learning, the energy put forth in order to accomplish learning tasks. Research has argued that student's cognitive and emotional engagement precedes their behavior (D'Mello & Graesser, 2011; Reschley & Christenson, 2012). Other research argues that emotion does not always cause behavior, but that the two work together within a feedback system regulated by cognition (Baumeister, Vohs, DeWall, & Zhang, 2007). Either way, there is strong reason to expect that behavior as manifest through log data is related to student's cognitive and emotional engagement.

The purpose of this project is to examine how log data from the LMS relate to student's responses from a self-report survey of their cognitive and emotional engagement. While previous work has used human observers to tie affective states to log data, we believe self-report is an appropriate measure to use for students' cognitive and emotional engagement. Appleton, Christenson, Kim, and Reschley (2006) argue that engagement as measured through observation "is highly inferential; therefore, obtaining the student perspective results in a more valid understanding of the student's experience and meaning in the environment" (p. 431). We will look at a variety of student's learning experiences, using activity-level self-report measures and log data from the LMS to identify student's cognitive and emotional engagement during specific learning activities. A strong relationship between the two sources of data will indicate how well log data can be used as a proxy measure for what can be obtained from self-report instruments.

Research Questions

The following research questions will be addressed by this project:

1. How do students' LMS log data relate to their responses on cognitive and emotional engagement scale scores from an activity-level student engagement survey?
2. How effectively can log data be used as a proxy measure of student engagement?

Method

Participants

This study analyzes the relationship of LMS log data and survey responses of undergraduate students from seven blended courses (14 sections) from two universities in the western United States. A range of courses were included in the study from general education to upper-level undergraduate courses in composition, educational technology, humanities, history, nursing, and web programming. All courses were offered in a blended format where seat time was reduced to allow for more online learning. IRB approval was obtained for the study. Three hundred and nineteen students volunteered to participate in the study during the Fall 2014 semester. While the majority of the students in each class chose to participate in the study, a small number did not, which may bias the results. Study participants were predominantly female (74.5%) between the ages of 21 and 25 (77.6%). The estimated majority race among our samples from both universities was Caucasian. Table 1 explains the number of participants from each course.

Measures

Student engagement was measured using the 7-item activity-level student engagement survey (see Article 2, instrument can be located in the Appendix). This survey assesses students' perceptions of their engagement in a specific learning activity. The survey contained both

Table 1

Number of Participants from Each Course

Course	Number of Participants
Composition (2 sections)	27
Educational Technology 1 (5 sections)	118
Educational Technology 2 (2 sections)	46
History (1 section)	56
Humanities (2 sections)	40
Nursing (1 section)	12
Web programming (1 section)	20
Total	319

cognitive and emotional engagement items. Responses to items were given using a 5-point Likert scale or 7-point semantic differential response scale. Appendix A contains the 7 engagement items from the activity-level student engagement survey.

Log data from the Canvas learning management system were collected for all 319 research participants. Log data records were obtained by submitting online requests to the Canvas application programming interface (API). Obtained records included the URLs of all course pages visited by participating students during the semester, time stamps of when each page was visited, the number of discussion posts or replies created, whether an assignment was turned in on time, and grades for each assignment. Two main variables were created using these data: page views and time spent on a page. Page view counts were created based on URLs. Time spent was calculated by taking the time stamp for a page and subtracting its value from the time stamp of the previous page. It's possible that an LMS page was open but students were not active on the page. While the product of this calculation is not a precise measure of actual time spent on a page, it does provide a meaningful starting point for capturing data on student engagement.

Additionally, some time-spent estimates may be especially misleading as Canvas does not force user logouts after a given amount of inactivity. If a student never logged out of Canvas, it could be hours or even days between one page view and another. To account for this, time spent scores were capped at a half-hour maximum in length. This cap is a general internet data analytics standard for studying user internet activity (Cooley, Mobashar, & Srivastava, 2013; Drutsa & Serdyukov, 2015). After reviewing the distribution of time spent on a page, we found that 89% of the data were less than half an hour in length (see Figure 1). This approach may not represent true activity that was occurring on a Canvas page for more than half an hour, but we believe this approach to be the most reasonable in representing time spent on a Canvas page.

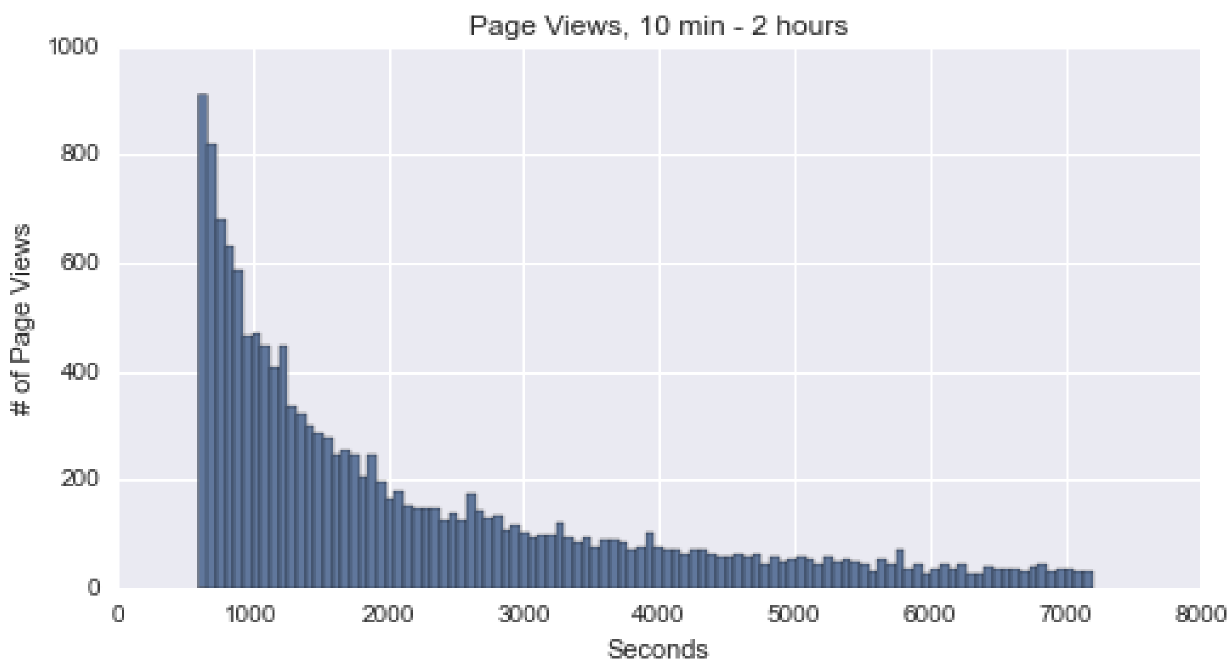


Figure 1. Distribution of page views between 10 minutes to 2 hours in length.

Student engagement survey data and log data were collected at three points during the semester (about mid-course, three-quarters of the way through the semester, and end of the semester, depending on the course). Researchers emailed a link to a student engagement survey and directed students to respond to their experience in a specified learning activity. Various online activities were selected for each course, including discussion boards, quizzes, exams, online videos, class projects, and essays (see Table 2). The portions of log data that corresponded to the chosen learning activities were extracted from the LMS. Survey data and log data were then paired for analysis.

Table 2

Number of Data Points at Each Time Point Broken Down by Learning Activity

Activity	# of data points at time point 1	# of data points at time point 2	# of data points at time point 3	Total # of data points
Quiz	72	0	76	148
Exam	0	12	0	12
Video	56	40	0	96
Writing assignment	27	47	27	101
Discussion	0	56	52	108
Project	46	46	46	138
Project + discussion	118	118	118	354

Analysis

The purpose of this study is to explore how log data are related to self-reported student engagement scores, signifying how well log can be used as an effective proxy measure for student engagement survey scores. This study was done using a cross-sectional correlation and regression analysis. Sections were created based on learning activities and time points. Time points could not be combined because many of the same students completed the same activity across time points, creating dependence in the data. Therefore, each time point is analyzed separately. The data from courses sharing the same type of learning activity were examined to determine whether data from each course could be combined and thereby increase sample size.

Structuring log data. Log data can be analyzed using different data structuring methods. Structure would include both the *amount* of log data to include as well as the *granularity* of the log data. Previous studies on LMS log data looked at engagement at the course-level, comparing all log data for a course to final grades (Macfadyen & Dawson, 2010; Morris, Finnegan, & Wu, 2005). This work provides little guidance when determining how much log data to include in activity-level analyses. One purpose of this study is to explore different methods of structuring log data to determine how to best study student engagement at the learning activity level using log data. Specifically, we manipulated the *amount* of log data to use and the *granularity* in defining the log data.

Amount of log data. One way the structure of log data can be changed is in the amount of log data used. We compared the differences between *one day's worth* of log data and *one week's worth*. From a pilot analysis, we found that most activity on the LMS occurs on the day that an assignment is due, though students who reported being more satisfied with a learning activity also tended to review an assignment page 24 hours or more before an assignment was due (Henrie et al., 2015). Looking at the log data from the day the student completed the assignment could provide a focused review of the most pertinent log data, while an extended amount of log data permits investigating the impact of previewing an assignment on student engagement. Additionally, extending log data to a week's worth accounted for complex activities that could require more than one day to complete.

Granularity of log data. In addition to determining how much log data to use, we also examined the merits of different granularities in log data. Specifically, we examined three types of granularities: 1. the *general* level, 2. the *LMS interaction type* level, and 3. *specific LMS pages* level. At the general level, we investigated the relationship between overall page views or time spent on the Canvas LMS during a given amount of time. We also looked at time spent and the number of page views on pages where students were learning as opposed to other types of LMS activity, such as navigating. While there could be any number of categories that could be created, we chose a framework based on the work of Borup, Graham, and Davies, 2013; Hawkins, Graham, Sudweeks, and Barbour, 2013; and Heinemann, 2005. This framework has three types of LMS interactions: learning, procedural, and social interactions. These categories comprise a number of different types of LMS pages, organized by the purpose of the page view. Table 3 defines and describes the three different types of LMS interactions and the specific types of pages that are included within each category.

Table 3

Hierarchy of LMS Activity Types and Page Views

Type of LMS Activity	Definition of Activity	Specific Types of Page Views Included
Learning Page Views	It is assumed that learning is taking place on these Canvas pages. These pages include assignment instructions, video or text instructional content, or spaces to submit assignments.	• Wikis • Assignments • Discussion board pages • Quizzes
Procedural Page Views	These pages include navigation points to important learning pages in Canvas as well as general learning management page views, such as viewing grades, checking assignment due dates on the calendar, or reviewing course policies in the syllabus.	• Modules page • Calendar • List of assignments • List of quizzes • List of discussion boards • Outcomes • Home page • People • Syllabus • Announcements • Grades • Profile
Social Page Views	These pages capture learner-to-learner or learner-to-instructor interactions that occur in discussion boards. This only has page views.	• Discussion board posts • Discussion board replies

Note. Canvas included a messaging system for students and instructors. These data could not be obtained from all courses, and were therefore left out altogether.

Finally, we structured log data to look at *target assignment page views, target assignment time spent,* and *target assignment previews*. Students responded in the engagement survey to a specified learning activity. The variable *target assignment page views* is the number of page views of the Canvas page where the targeted learning activity took place, and *target assignment time spent* is the amount of time spent on those pages. *Target assignment previews* was the number of times a student visited the targeted learning activity assignment page at least 24 hours before the assignment was submitted. We hypothesize that these three variables represent the most direct log data information about student engagement in the targeted learning activity. The latter was particularly included because of results from a pilot study that suggested that students who were more satisfied with their learning experience previewed an assignment page well before it was due (Henrie, Bodily, Manwaring, & Graham, 2015).

Correlation analysis. Log data variables were first correlated to student engagement survey scores to understand how each variable relates to self-reported cognitive and emotional engagement. This was done cross-sectionally, analyzing data from one activity type at one time point at a time. All log data variables under a given structuring method were correlated to cognitive and emotional engagement scores from the self-report survey using bivariate Pearson correlation analysis, based on whether log data and engagement scores meet the statistical assumptions of data independence, normal distribution and linearity. Table 4 describes the different correlational analyses conducted for a given activity at a specific time point. Overall, cognitive engagement and emotional engagement survey scores were correlated with 22 log data variables (11 log data variables from 1 day's worth of log data and 11 from 1 week's worth of log data) for seven different courses. Strength of relationships between specific log data variables and cognitive or emotional engagement were explored by considering the strength and statistical significance of correlations. This was done to understand how log data are uniquely related to cognitive or emotional engagement. Strengths of correlations were also considered to determine which log data structuring method was most useful for studying activity-level log data and student engagement.

Table 4

Correlation Analyses to Be Done for Data from a Given Activity at a Specific Time Point

	Log Data Structures					
	General Level		LMS Interaction Type Level		Target Assignment Level	
	1 Day	1 Week	1 Day	1 Week	1 Day	1 Week
Cognitive Engagement	Total page views and time spent	Total page views and time spent	Page views and time spent on Learning, Procedural, and Social pages	Page views and time spent on Learning, Procedural, and Social pages	Page views and time spent on different types of LMS pages	Page views, time spent, and previews on target assignment pages
Emotional Engagement	Total page views and time spent	Total page views and time spent	Page views and time spent on Learning, Procedural, and Social pages	Page views and time spent on Learning, Procedural, and Social pages	Page views and time spent on different types of LMS pages	Page views, time spent, and previews on target assignment pages

Previous research in comparing self-report student engagement data to other measurement methods have generally found low to moderate correlations (r = 0.15 – 0.43; see Fredricks, Blumenfeld, & Friedel, 2005; Fredricks & McColskey, 2012; Skinner, Kindermann, & Furrer, 2009). These comparisons were between student self-report and teacher observations of student engagement. The more internal aspects of student engagement, like emotional engagement, tended to have lower correlations in these studies (0.15 – 0.20). This is likely due to the challenge of accurately identifying someone else’s emotions through observation (Skinner et al., 2009). In our review of the literature, we were unable to find reported correlations between self-reported engagement and other types of student engagement data. In order for log data to act as a reliable proxy for students' self-reported cognitive and emotional engagement, a strong correlation between the log data and survey responses would need to exist. We expected to find stronger correlations between self-report and log data than what was found with teacher observations as we relied on students' own behavior rather than the observations of others.

Regression analysis. If significant, meaningful correlations were found between log data and survey scores then regression analyses would then be attempted. Cognitive and emotional engagement survey scores would be regressed on key log data variables. Key log data variables were made up of those log data variables that had significant correlations with cognitive or emotional engagement. Typically, a regression analysis makes an inference on causality. In this case, we are careful to claim that we are *not* inferring causality in the direction implied by the regression analysis, where log data would *cause* cognitive and emotional engagement. In deed, we assert that the *opposite* is true: that cognitive and emotional engagement likely lead to behavior as observed by log data.

The purpose of this regression analysis was to determine how well behavior, as measured in log data, could act as a proxy measure for perceived emotional and cognitive engagement, as measured through self-report. This would be done by considering the size and statistical significance of the R^2 of the overall regression model. The R^2 indicates how approximate log data represents self-report scores. A low R^2 would mean that log data do not represent self-report scores very well, whereas a high R^2 (> 0.50) would mean that log data can more accurately represent how students would respond on a self-report measure of their cognitive or emotional engagement. Like the correlation analysis, the regression analysis would be done cross-sectionally by activity within a specific time point. Cognitive engagement scores would be predicted separate from emotional engagement scores, rather than done together through path analysis as causal relationships are not the interest of this study.

Results

Review of Descriptive Statistics

Of the 319 students who consented to participate in the study, only 201 completed at least one of the three student engagement surveys. An additional four dropped the course before the end, which removed their log data from the system. This left data for 197 participants, for a completion rate of 62% (for course by course completion rate, see Table 5). From the remaining 197 participants, the response rate varied across time points. Time point 1 had an 89% completion rate, time point 2 had a 70% completion rate, and time point 3 had a 75% completion rate. Survey scores were calculated using a model developed through confirmatory factor analysis in Article 2, with Maximum Likelihood Rubust (MLR) estimation used to estimate missing data from the 201 study participants. See Tables 6, 7, and 8 for descriptive statistics of student engagement survey results.

Table 5

Actual Participation Rate by Course

	# of students who signed a consent form	# of actual participants	Completion rate
Educational Technology 1	118	75	64%
Educational Technology 2	46	31	67%
English	27	9	33%
History	56	47	84%
Humanities	39	14	35%
Nursing	12	9	75%
Web Development	20	12	60%
Total	318	197	62%

Table 6

Log Data and Survey Descriptives for Time Point 1

	N	Min	Max	Mean	St. Dev.
Educational Tech. 1 (Project/Discussion)					
Cognitive Engagement	75	-0.95	1.14	0.15	0.45
Emotional Engagement		-1.40	1.66	0.17	0.65
Target Assignment Page Views		0	19	5.63	3.44
Target Assignment Time Spent		0	276.97	68.04	42.81
Educational Tech. 2 (Project)					
Cognitive Engagement	31	-0.66	0.86	0.16	0.39
Emotional Engagement		-0.89	1.30	0.29	0.58
Target Assignment Page Views		1	20	4.26	3.33
Target Assignment Time Spent		0.42	120	58.54	27.23
English (Writing Assignment)					
Cognitive Engagement	9	-1.19	0.11	-0.22	0.43
Emotional Engagement		-1.81	0.58	-0.33	0.73
Target Assignment Page Views		1	6	3.78	1.39
Target Assignment Time Spent		0.12	68.27	37.50	26.20
History (Video)					
Cognitive Engagement	47	-1.60	1.04	-0.25	0.60
Emotional Engagement		-1.96	1.39	-0.17	0.82
Target Assignment Page Views		0	9	1.89	2.05
Target Assignment Time Spent		0	120.83	26.78	33.10
Humanities (Quiz)					
Cognitive Engagement	14	-0.85	0.78	0.01	0.43
Emotional Engagement		-1.09	0.93	-0.07	0.66
Target Assignment Page Views		5	12	7.64	1.95
Target Assignment Time Spent		1.98	59.20	14.10	17.81
Nursing (Quiz)					
Cognitive Engagement	9	-0.95	-0.06	-0.43	0.26
Emotional Engagement		-1.61	-0.26	-0.68	0.42
Target Assignment Page Views		5	6	5.33	0.50
Target Assignment Time Spent		3.37	32.10	12.98	10.55
Web Development (Quiz)					
Cognitive Engagement	12	-0.17	0.88	0.13	0.28
Emotional Engagement		-0.41	0.94	0.04	0.34
Target Assignment Page Views		0	37	31.58	9.99
Target Assignment Time Spent		0	136.57	43.72	37.89

Note. Time spent is measured in minutes.

Table 7

Log Data and Survey Descriptives for Time Point 2

	N	Min	Max	Mean	St. Dev.
Educational Tech. 1 (Project/Discussion)					
Cognitive Engagement	75	-1.08	1.14	0.21	0.45
Emotional Engagement		-1.44	1.66	0.32	0.62
Target Assignment Page Views		0	15	5.72	3.31
Target Assignment Time Spent		0	131.02	33.62	27.15
Educational Tech. 2 (Project)					
Cognitive Engagement	31	-0.83	0.68	0.03	0.31
Emotional Engagement		-0.84	1.11	0.06	0.42
Target Assignment Page Views		1	9	3.52	1.96
Target Assignment Time Spent		0.20	150.13	46.78	35.12
English (Writing Assignment)					
Cognitive Engagement	9	-0.36	0.16	-0.11	0.16
Emotional Engagement		-1.40	0.32	-0.23	0.64
Target Assignment Page Views		3	8	4.89	1.90
Target Assignment Time Spent		0.65	150.38	37.79	44.11
History (Discussion)					
Cognitive Engagement	47	-1.60	0.93	-0.03	0.49
Emotional Engagement		-1.96	1.35	0.03	0.66
Target Assignment Page Views		0	13	3.13	2.98
Target Assignment Time Spent		0	60.67	17.83	19.69
Humanities (Video)					
Cognitive Engagement	14	-1.45	0.49	-0.12	0.45
Emotional Engagement		-1.55	0.84	-0.09	0.60
Target Assignment Page Views		5	11	8.07	2.23
Target Assignment Time Spent		0.88	48.65	14.24	16.50
Nursing (Exam)					
Cognitive Engagement	9	-0.34	0.00	-0.10	0.14
Emotional Engagement		-1.39	0.00	-0.33	0.52
Target Assignment Page Views		5	10	6.67	1.66
Target Assignment Time Spent		4.58	63.52	27.98	23.22
Web Development (Writing Assignment)					
Cognitive Engagement	12	-0.62	0.35	-0.10	0.26
Emotional Engagement		-0.83	0.52	-0.13	0.33
Target Assignment Page Views		0	8	3.50	2.20
Target Assignment Time Spent		0	36.02	11.35	14.16

Note. Time spent is measured in minutes.

Table 8

Log Data and Survey Descriptives for Time Point 3

	N	Min	Max	Mean	St. Dev.
Educational Tech. 1 (Project/Discussion)					
Cognitive Engagement	75	-0.96	1.14	0.02	0.40
Emotional Engagement		-1.40	1.66	0.01	0.59
Target Assignment Page Views		0	18	6.64	4.29
Target Assignment Time Spent		0	148.85	66.43	34.18
Educational Tech. 2 (Project)					
Cognitive Engagement	31	-1.60	1	-0.04	0.59
Emotional Engagement		-1.96	1.27	-0.06	0.73
Target Assignment Page Views		1	12	4.03	2.20
Target Assignment Time Spent		8.32	120.82	61.69	27.22
English (Writing Assignment)					
Cognitive Engagement	9	-1.56	0.55	-0.25	0.57
Emotional Engagement		-1.86	1.02	-0.42	0.78
Target Assignment Page Views		4	12	7.89	2.80
Target Assignment Time Spent		3.02	95.68	54.82	31.70
History (Quiz)					
Cognitive Engagement	47	-1.35	0.86	-0.04	0.51
Emotional Engagement		-1.54	1.40	-0.13	0.71
Target Assignment Page Views		11	35	16.83	5.42
Target Assignment Time Spent		6.03	62.86	21.61	14.57
Humanities (Discussion)					
Cognitive Engagement	14	-0.83	0.31	-0.03	0.31
Emotional Engagement		-1.33	0.74	0.01	0.52
Target Assignment Page Views		8	11	8.79	1.05
Target Assignment Time Spent		1.62	50.30	11.80	14.53
Nursing (Discussion)					
Cognitive Engagement	9	-1.21	0.14	-0.43	0.45
Emotional Engagement		-1.82	0.00	-0.70	0.61
Target Assignment Page Views		2	6	3.89	1.54
Target Assignment Time Spent		0.02	0.08	0.05	0.03
Web Development (Quiz)					
Cognitive Engagement	12	-0.23	0.40	-0.02	0.17
Emotional Engagement		-0.46	.41	0.01	0.20
Target Assignment Page Views		0	36	28.67	13.41
Target Assignment Time Spent		0	122.67	44.11	34.26

Note. Time spent is measured in minutes.

We reviewed the log data to determine whether they was suitable for analysis. We compared the distribution of log data between the 1-day data set and the 7-days data set. We found that many students completed their work within 24 hours of the due date, but not all. In one course, most students had completed the assignment well before 24 hours of the assignment due date (see Figures 2 and 3). Because of this limitation, we only compare 1 day's worth of log data to 7 days' worth for those courses where most students participated in the target assignment 24 hours before the due date.

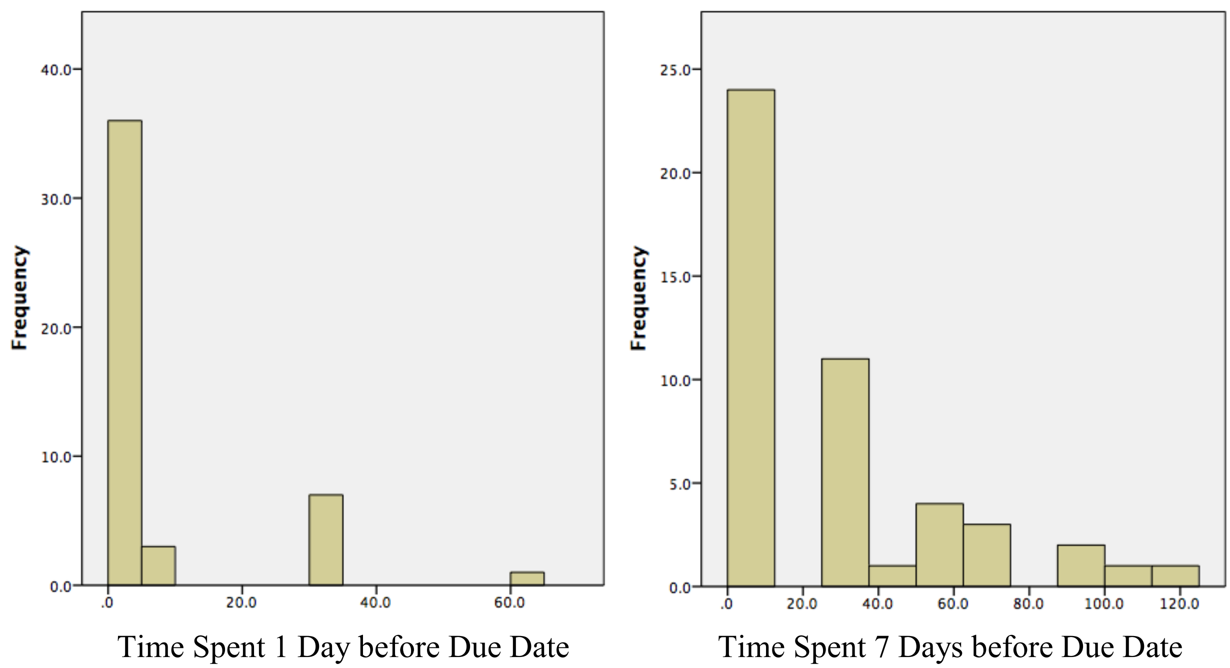
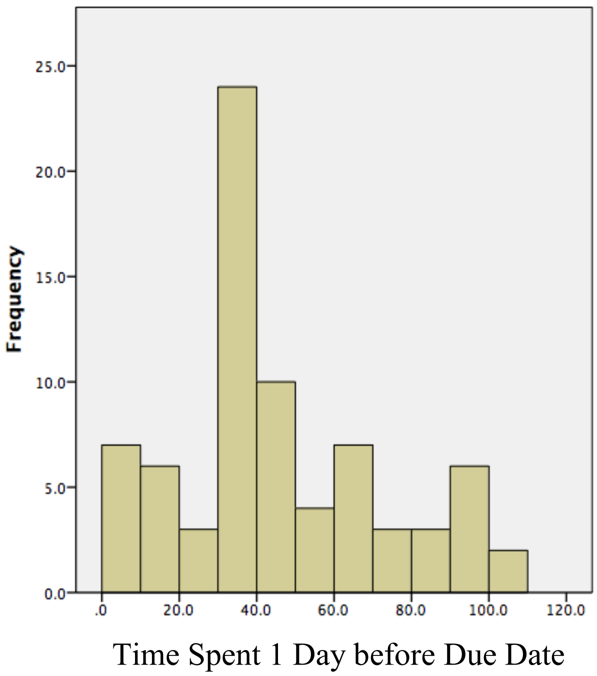


Figure 2. Comparison of time spent on target assignment for 1 day and 7 days before the assignment due date for the history course. Time spent is in minutes.



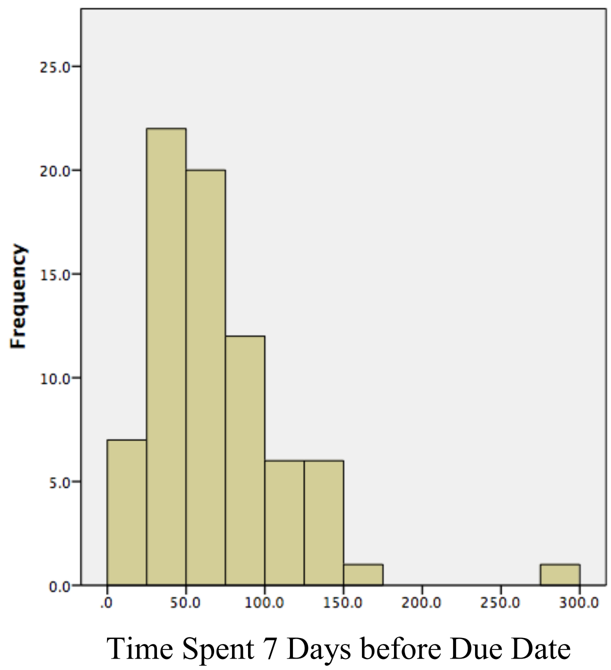


Figure 3. Comparison of time spent on target assignment for 1 day and 7 days before the assignment due date for an educational technology course. Time spent is in minutes.

It was necessary to try and combine the data of some courses that shared a similar learning activity in order to have a sufficient sample size. Table 9 describes which learning activities were completed for each course at each of the three time points. To determine whether data from multiple courses doing the same activity could be reasonably combined, we compared the distribution of page views, time spent, and cognitive and emotional engagement on the target assignment in each course being considered. For example, the history, humanities, nursing, and web development courses all had students complete a quiz. Looking at descriptive statistics and box plots for these courses on log data and student engagement survey scores, it was determined that the learning experiences were too unique for each course to reasonably combine the data (see Figures 4 & 5). This was true for other courses sharing the same type of learning activity. Because data across courses couldn't be combined, we chose to pursue the correlation analysis for the three largest courses (educational technology 1 and 2, and history). These three courses had a meaningful sample size for statistical analysis (n > 30), and provided a range of learning experiences that could help us determine how behavior matched emotional and cognitive states.

Table 9

Learning Activities Completed for Each Course at Each Time Point

	Time Point 1	**Time Point 2**	**Time Point 3**
Education Technology 1	Project Presentation & Discussion	Project Presentation & Discussion	Project Presentation & Discussion
Educational Technology 2	Project	Project	Project
English	Writing Assignment	Writing Assignment	Writing Assignment
History	Video	Discussion	Quiz
Humanities	Quiz	Video	Discussion
Nursing	Quiz	Exam	Discussion
Web Development	Quiz	Writing Assignment	Quiz

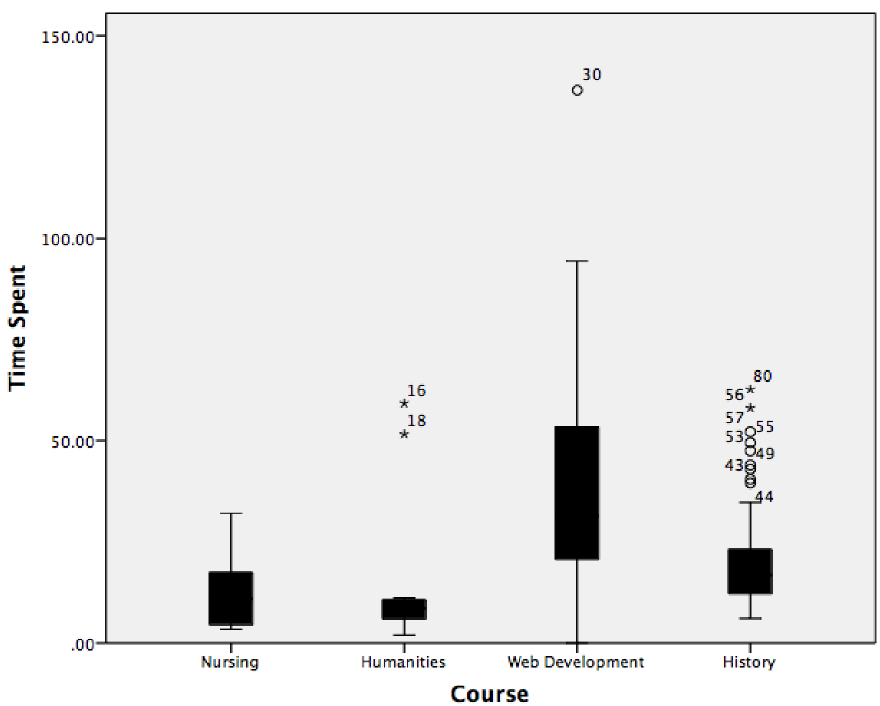


Figure 4. Time spent on a quiz assignment for four different courses. Time spent is measured in minutes.

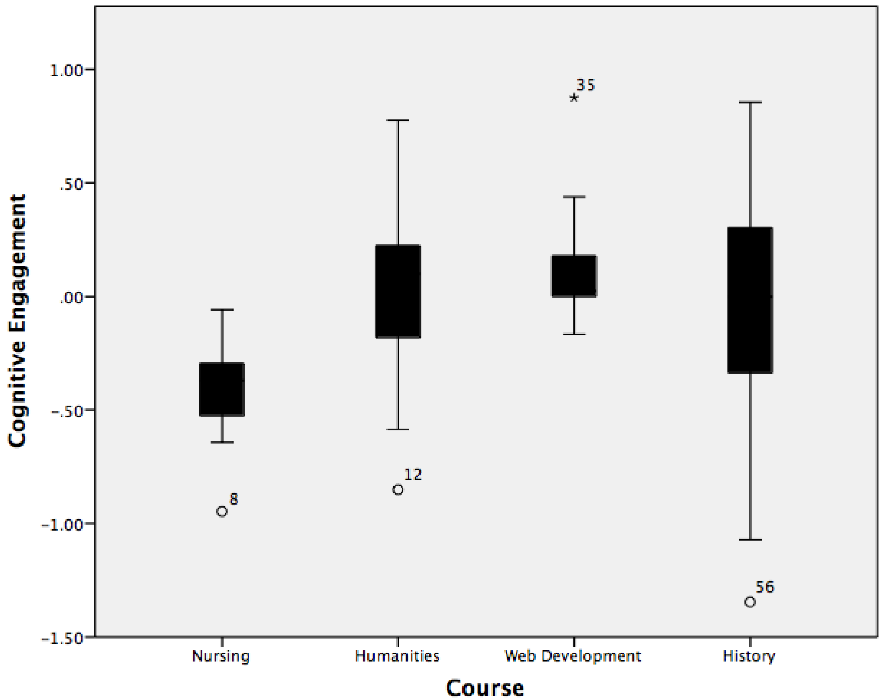


Figure 5. Self-reported cognitive engagement during a quiz for four different courses.

Checking Statistical Assumptions

We reviewed the distribution and presence of outliers for both the log data and the survey data to determine whether the data met the assumptions for the Pearson's correlational analysis. About half of the variables had normal distributions (see Figure 6), while others did not (see Figure 7). For the variables that did not have a normal distribution, Spearman's nonparametric correlational analysis was used instead of Pearson's. Some variables also had significant outliers. These outliers were removed so as not to bias the results. We also investigated scatter plots for nonlinear relationships and found nothing of concern.

Correlation Analysis

Students' cognitive and emotional engagement survey scores were each correlated with the LMS log data variables. The analysis was done course by course for the three courses that

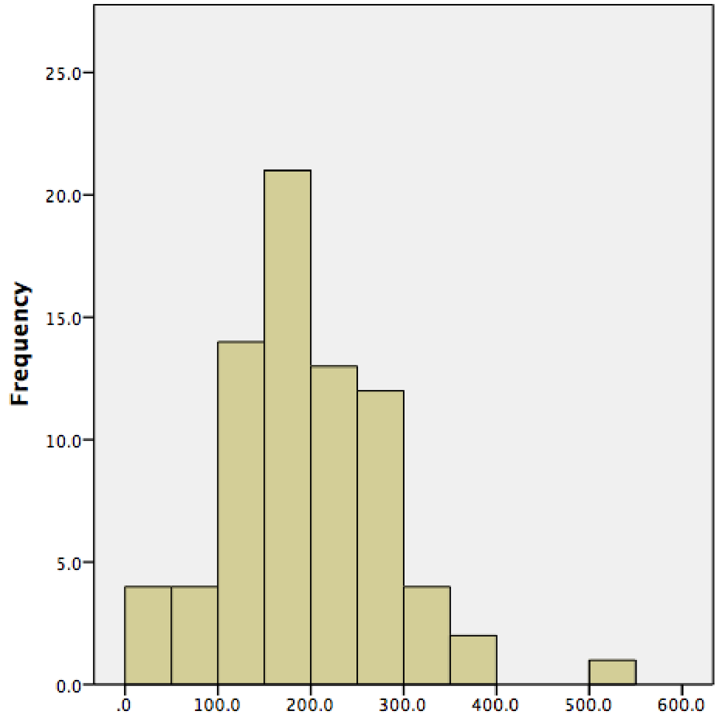


Figure 6. Distribution of total time spent on the LMS at time point 1.

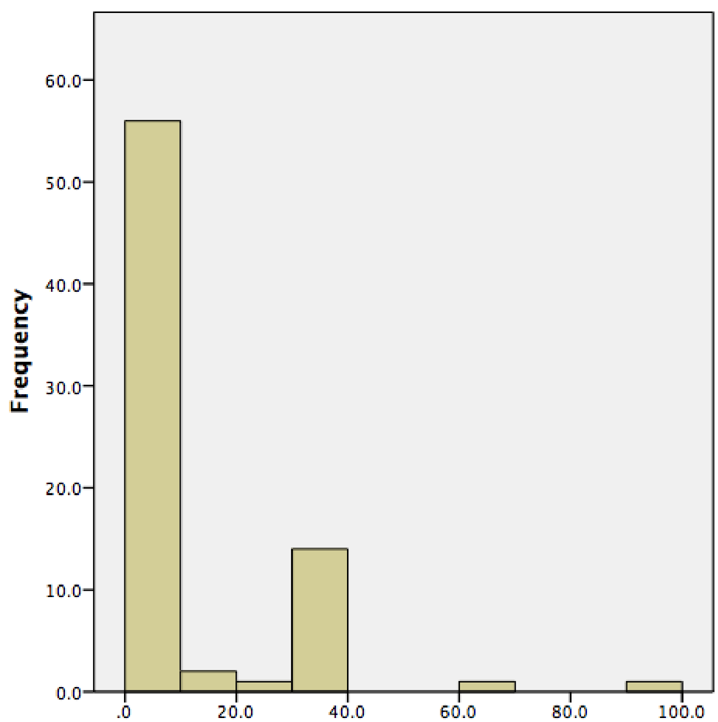


Figure 7. Distribution of time spent on procedural pages at time point 1.

had a meaningful sample size (history, educational technology 1, and educational technology 2). The difference in strength of correlation between using log data from seven days before the assignment due date to one day before the assignment due date was tested, as well as differences among the three levels of log data granularity (see Table 4).

Overall, there were very few significant correlations between survey scores and log data. The highest correlation was in the educational technology 1 course between cognitive engagement and time spent on Learning Pages ($r = 0.377$, $p < .05$). This correlation was considered to be moderate. There were no significant correlations between the log data variables and student engagement survey scores for the history or educational technology 2 courses. Tables 10, 11, and 12 show correlation data for each of the three courses for the 7-day period. Looking at the correlation results from the educational technology course 1, time spent variables tended to have a stronger relationship with the survey scores than the page view variables. The difference between using 1 day's worth of log data and 7 days was tested in the educational technology 2 class, as this was the only course with significant correlations and a significant number of students working on the assignment within 24 hours of the due date. The correlations were stronger for the 7-day period log data set than the 1-day period (see Table 13).

Overall, the strength of the observed correlations indicates the absence of a simple linear relationship between the amount of activity and time spent on the LMS and cognitive and emotional engagement. Examining scatterplots between log data variables and survey scores revealed possible clusters based on unobserved variables that might better help explain the relationship between log data and survey scores (see Figure 8). For example, students who are experiencing frustration may be spending more time trying to understand an assignment and dropping on their emotional engagement.

Table 10

Correlations Between Log Data from a 7-Day Period and Associated Student Engagement Survey Scores from a History Course

	Total Page Views	Total Time Spent (in minutes)	Learning Page Views	Learning Time Spent (in minutes)	Procedural Page Views	Procedural Time Spent (in minutes)	Social Page Views	Target Page Views	Target Time Spent (in minutes)	Previews
Cognitive Engagement at Time Point 1 n = 47	0.173	-0.007	0.130	-0.056	0.190	0.212	0.123	0.074	0.036	0.059
Emotional Engagement at Time Point 1 n = 47	0.095	-0.025	0.064	-0.061	0.086	0.163	0.088	0.114	0.079	0.044
Cognitive Engagement at Time Point 2 n = 47	0.168	0.129	0.111	0.104	0.222	0.067	0.106	0.240	0.273	0.152
Emotional Engagement at Time Point 2 n = 47	0.122	0.077	0.079	0.160	0.158	-0.152	0.097	0.212	0.230	0.071
Cognitive Engagement at Time Point 3 n = 47	0.098	0.006	0.079	-0.046	0.105	0.078	-0.106	0.038	-0.010	0.058
Emotional Engagement at Time Point 3 n = 47	0.073	0.028	0.077	0.050	0.077	-0.013	0.026	-0.027	-0.047	0.042

Note. * $p < .05$; ** $p < .01$. For brevity, the log data variables for each time point are listed in the same column rather than in separate columns. Log data for each time point correspond with the engagement survey responses at each time point.

Table 11

Correlations Between Log Data from a 7-Day Period and Associated Survey Scores from Educational Technology Course 1

	Total Page Views	Total Time Spent (in minutes)	Learning Page Views	Learning Time Spent (in minutes)	Procedural Page Views	Procedural Time Spent (in minutes)	Social Page Views	Target Page Views	Target Time Spent (in minutes)	Previews
Cognitive Engagement at Time Point 1 n = 75	0.244*	0.306**	0.234*	0.308**	0.220	0.199	0.021	0.091	0.023	0.065
Emotional Engagement at Time Point 1 n = 75	0.218	0.250*	0.224	0.255*	0.186	0.120	-0.032	0.142	-0.016	0.063
Cognitive Engagement at Time Point 2 n = 75	0.214	0.333**	0.258*	0.377*	0.057	-0.093	0.108	-0.083	0.142	0.159
Emotional Engagement at Time Point 2 n = 75	0.185	0.289*	0.224	0.325**	0.054	-0.088	0.083	-0.110	0.135	0.162
Cognitive Engagement at Time Point 3 n = 75	-0.059	0.061	-0.018	0.002	-0.057	0.061	0.239*	-0.162	-0.150	-0.135
Emotional Engagement at Time Point 3 n = 75	-0.060	0.014	0.014	-0.046	-0.125	0.010	0.256*	-0.144	-0.204	-0.156

Note. * $p < .05$; ** $p < .01$. For brevity, the log data variables for each time point are listed in the same column rather than in separate columns. Log data for each time point correspond with the engagement survey responses at each time point.

Table 12

Correlations Between Log Data from a 7-Day Period and Associated Survey Scores from Educational Technology Course 2

	Total Page Views	Total Time Spent (in minutes)	Learning Page Views	Learning Time Spent (in minutes)	Procedural Page Views	Procedural Time Spent (in minutes)	Social Page Views	Target Page Views	Target Time Spent (in minutes)	Previews
Cognitive Engagement at Time Point 1 n = 31	-0.141	0.066	-0.160	0.002	-0.011	-0.030	.	-0.142	-0.060	-0.060
Emotional Engagement at Time Point 1 n = 31	-0.017	0.267	0.046	0.180	0.049	0.089	.	-0.054	0.114	0.063
Cognitive Engagement at Time Point 2 n = 31	-0.040	0.026	0.013	-0.041	-0.071	-0.096	.	0.088	0.075	-0.139
Emotional Engagement at Time Point 2 n = 31	-0.018	0.080	0.027	-0.011	-0.046	-0.166	.	0.107	0.080	-0.109
Cognitive Engagement at Time Point 3 n = 31	-0.274	-0.086	-0.110	0.015	-0.217	-0.102	.	-0.017	-0.115	0.129
Emotional Engagement at Time Point 3 n = 31	-0.269	-0.034	-0.034	0.091	-0.251	-0.207	.	0.074	-0.110	0.134

Note. * $p < .05$; ** $p < .01$. For brevity, the log data variables for each time point are listed in the same column rather than in separate columns. Log data for each time point correspond with the engagement survey responses at each time point.

Table 13

Correlations Between Log Data from a 1-Day Period and Associated Survey Scores from Educational Technology Course 1

	Total Page Views	Total Time Spent (in minutes)	Learning Page Views	Learning Time Spent (in minutes)	Procedural Page Views	Procedural Time Spent (in minutes)	Social Page Views	Target Page Views	Target Time Spent (in minutes)	Previews
Cognitive Engagement at Time Point 1 n = 75	0.153	0.205	0.132	0.219	0.060	0.029	-0.047	0.125	0.119	0.073
Emotional Engagement at Time Point 1 n = 75	0.212	0.265*	0.205	0.278*	0.116	0.025	0.002	0.189	0.098	0.081
Cognitive Engagement at Time Point 2 n = 75	-0.025	0.103	-0.037	0.117	-0.029	-0.122	-0.067	-0.132	0.054	0.046
Emotional Engagement at Time Point 2 n = 75	-0.006	0.071	-0.039	0.087	-0.001	-0.074	-0.076	-0.127	0.045	0.042
Cognitive Engagement at Time Point 3 n = 75	-0.015	0.177	0.109	0.194	-0.027	-0.019	0.227*	-0.037	0.114	-0.062
Emotional Engagement at Time Point 3 n = 75	-0.037	0.114	0.091	0.135	-0.120	-0.078	0.227	-0.040	0.048	-0.068

Note. * $p < .05$; ** $p < .01$. For brevity, the log data variables for each time point are listed in the same column rather than in separate columns. Log data for each time point correspond with the engagement survey responses at each time point.

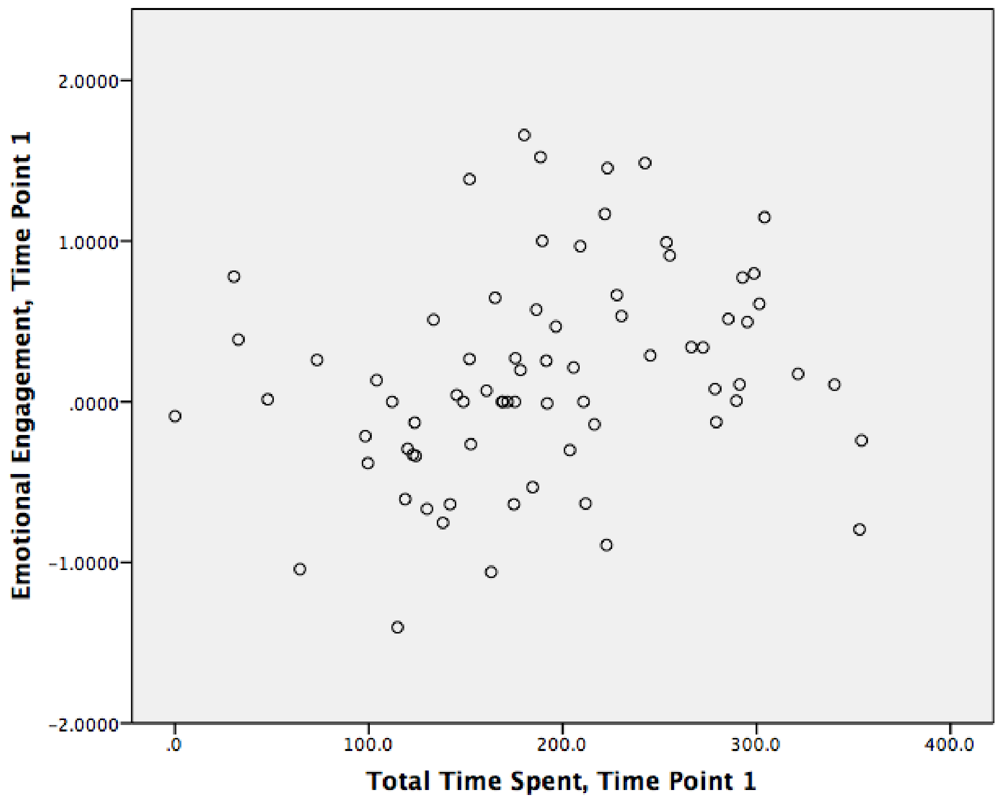


Figure 8. Scatterplot of emotional engagement and total time spent at time point 1.

Because no strong correlations were found between the survey measures and log data, we determined it was not appropriate to conduct regression analysis to try and predict survey scores using the LMS log data.

Discussion

The purpose of this study was to determine whether LMS log data could be used as a proxy for student engagement survey scores. Students' cognitive and emotional engagement is essential for deep learning, persistence, and satisfaction. Furthermore, this internal energy ultimately takes a physical manifestation as learners engage in learning activities. We have used self-report data to measure students' cognitive and emotional engagement. There is a significant cost in collecting engagement data using this method: namely that learning is disrupted in order to take the survey, and it requires the cooperation and contribution of students to obtain the data. Our hypothesis was that LMS log data would stand as a useful proxy of students' emotional and cognitive engagement as measured through self-report. The results of our study to test this hypothesis were mixed, showing that log data could potentially make a moderately useful proxy.

Overall, we found very few correlations between the student engagement survey data and the LMS log data. Significant correlations were found in only one course, and none of those correlations were very strong. There are several possible reasons for this. For example, our findings may have been affected by weaknesses in the design of our study. While significant effort was made to get a sufficiently large sample, we struggled to get enough completed surveys. This is always a limitation when trying to gather self-report data. We only found significant correlations in one course, which happened to be the largest sample. Increasing the sample size may be needed to better study the relationship between engagement self-report data and log data.

Our method of collecting the log data may also have impacted the results observed in this study. We chose to use log data from 1 day as well as 7 days from the assignment due date, with the assumption that most, if not all, learning activity was occurring during that time. In a pilot study (Henrie, Bodily, Manwaring, & Graham, 2015), we found that most activity occurred within 24 hours of the due date. However, looking at our descriptive statistics (see Tables 6, 7, and 8), it is possible that students in this study did their work well before 1 day and even 7 days before an assignment was due, or didn't work on the assignment until after the due date. Depending on how much this occurred, this could significantly affect our ability to detect a significant relationship between survey data and log data.

We chose to use due dates as the cut-off time because it was a more practical approach. Another approach would be to go off the date an assignment was submitted, particularly since one of the LMS pages in Canvas is a submission confirmation page. However, this would only work if the learning activity required something to be submitted to the LMS. This is not the case for discussion boards, or when viewing content pages or videos. One could go off the last date the page was visited, but it is possible that students revisit pages long after they actually engaged in the activity, such as when reviewing content before an exam. It would require significant manual work to review the log data and determine when engagement in the learning activity likely occurred. This approach would not scale well to large data sets. These are real limitations when the purpose is to study student engagement at the activity level using log data. Still, we are confident that our approach likely recorded much of the actual engagement in the learning activities we studied.

Another explanation for the results we observed is that students' prior knowledge and abilities may have impacted the amount of time required to successfully complete the assignment. Some students may have needed less time than others to successfully complete the activity because of prior skill or experience. Students with less knowledge or skill may have needed substantially more time to understand and complete the assignment. This would prevent a strong linear relationship from existing between time spent or page views and survey data. Having more information about students' prior abilities could better delineate the relationship between self-reported and observed engagement.

Comparing self-report to observational data may also have impacted the results we obtained. Studies that have compared self-report data to observational data have found mixed results. Prince et al. (2008) conducted a systematic review of 187 studies that compared observational data to self-report data in measuring physical activity in adults. They found that the correlation between the two sources of data ranged from -0.71 to 0.96, indicating that comparisons can be quite mixed. Elliot (2004) also found disparities when comparing survey data on students' locus of control to data from interviews and observations. Using self-report data has several limitations, including the possibility that participants do not respond accurately out of shame, or because they do not understand the survey questions (see Elliot, 2004; Gobert, Baker, & Wixon, 2015).

In previous research of student engagement, weak to moderate correlations were found between students' self-reported engagement and teacher's reports of student engagement ($r = 0.15 – 0.43$; see Fredricks, Blumenfeld, & Friedel, 2005; Fredricks & McColskey, 2012; Skinner, Kindermann, & Furrer, 2009). We expected that students' own behavior as measured through the log data would have a stronger relationship with their survey scores than a teacher's observation of student behavior. Instead, we found comparable relationships (see Tables 10 – 12). Stronger correlations would be preferred when seeking for a meaningful proxy measure, but our findings were similar to previous research comparing different measures of student engagement.

There are also limitations in treating Likert scale items, such as those used in the survey for this study, as interval data, where the amount of change between units is considered equivalent. Comparing data obtained through Likert scales, where the data are considered "ordinal at best" may not match well to data that is interval, such as time spent on or page views of an assignment (Fulmer & Frijters, 2009). Significant effort was put in to develop a valid measure of student engagement (see Article 2). The measure we used was founded in existing engagement research and scale development. Our model of students' cognitive and emotional engagement fit the data well (RMSEA = 0.050, CFI = 0.985, TLI = 0.971, SRMR = 0.033). If we assume that the self-report instrument is a valid measure of student's cognitive and emotional engagement, then this study gives good evidence that LMS log data would not make a good proxy measure. Other types of log data may be useful to explore. For instance, it is possible to plug in external tools into some LMSs (such as Canvas) for mouse tracking. Baker et al. (2012) had better success when comparing log data obtained from an intelligent tutoring system to data obtained from human observers in detecting student engagement. D'Mello and Graesser (2012) had similar results in their work in comparing log data from an intelligent tutoring system to data collected from physiological sensors on students' affective states. These methods hold promise, but assume that internal aspects of engagement, such as emotion, are being validly measured through observation or physiological detection. Future research needs to continue to address the challenges of comparing data obtained through different methods.

A final interpretation of our findings that will be mentioned here is that student engagement is a complicated construct, and that the internal and behavioral factors are related but not the same thing. Many conceptualizations of student engagement include a behavioral component in addition to emotional and cognitive engagement. Behavioral engagement has varying definitions, ranging from the amount of involvement in class activities to conforming to school rules and expectations (see Fredricks et al., 2004). In Reeve and Tseng (2011) behavioral engagement had a 0.42 correlation with emotional engagement and 0.59 with cognitive engagement. Skinner, Kindermann, and Furrer (2009) found a 0.60 correlation between behavioral engagement and emotional engagement. All engagement factors in both of these studies were measured through self-report rather than observation. The significant correlations observed in our study between the log data and survey data are fairly comparable (see Table 11), even though we compared self-report to observational data. This finding, however, is limited because the correlations were only observed in one of our three samples.

In the correlations we did observe, it was interesting to find that the stronger correlations were with time spent variables and at the Learning Page View level. At the outset, it would have seemed likely that activity on the target assignment page would correspond most closely to self-reported engagement in that assignment. Learning Page Views included activity on other assignment pages unrelated to the target assignment. This may mean that student's engagement at the activity level is influenced by the combined learning experience: that a student may not be particularly interested in one assignment, but the excitement or interest from another carries over into the current learning activity. Lawson and Lawson (2013) have argued that engagement research needs to more carefully consider the whole student experience: not just what occurs in the classroom, but also outside of the classroom, including home and social life. This could also imply that engagement in one specific experience cannot be isolated from other experiences surrounding the activity. Our findings, while limited, tend to support this argument.

Interest in educational data collected from computer systems, big data, and learning analytics is growing (Bienkowski, Feng, & Means, 2012; Ferguson, 2012; Siemens, 2013). These data have helped us explore learning in unimaginable ways. Log data are an abundant source of in-the-moment activity data with potential to help us better understand the phenomenon of learning with minimal interference to the student. Future exploration is needed, however, to understand the value of these data. In terms of using LMS log data to inform us about cognitive and emotional engagement, we came across significant limitations and challenges. In-the-moment behavior captured through log data may be more complex than we realize. Simply spending more time or having more activity on an assignment does not necessarily mean positive student engagement. Other factors need to be accounted for to better understand what it means to be effectively engaged in learning, such as previous knowledge and abilities, motivation to learn, or level of confusion or frustration. Further work with other methods for measuring student engagement, like mouse tracking, physiological instruments, or human observers may also yield valuable results.

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Appendix

Emotional Engagement Scale

1. Did you enjoy this activity? Not at all 1 2 3 4 5 Very Much
2. Was this activity interesting? Not at all 1 2 3 4 5 Very Much
3. Did you wish you had been doing something else? Not at all 1 2 3 4 5 Very Much
4. Describe your mood during this activity: Excited 1 2 3 (Neither 4) 5 6 7 Bored

Cognitive Engagement Scale

5. How well were you concentrating? Not at all 1 2 3 4 5 Very Much
6. Describe your mood during this activity: Passive 1 2 3 (Neither 4) 5 6 7 Active
7. Describe your mood during this activity: Focused 1 2 3 (Neither 4) 5 6 7 Distracted

DISSERTATION CONCLUSION

The purpose of this study was to explore methods for measuring student engagement in technology-mediated learning experiences, particularly to explore innovative methods for measuring engagement. The ultimate goal was to identify measurement approaches that would allow us to study learning in the moment, that could be scalable, and that would minimize the disruption to the student in obtaining the data.

In Article 1, we examined what has been done to measure student engagement in technology-mediated learning experiences. The most common method used was self-report. Self-report approaches have distinct advantages. They are easy to scale to large sample sizes. There are established statistical instrument evaluation methods, such as confirmatory factor analysis, that can be used to test theory and the reliability of the survey instrument across samples. Self-report is also considered a more valid approach for measuring internal psychological phenomena. However, self-report approaches are disadvantaged in that learners must be disrupted from learning to obtain the needed data.

Other studies we reviewed used observation, user activity data from learning systems, and physiological instruments to measure student engagement. Each of these methods has their own strengths and limitations. We were particularly intrigued by the potential of the trace data from learning systems as a source of student engagement data. These data are created as learners interact with the system and can be obtained with no disruption to the learner. It also provides in-the-moment information about learner behavior. Further, learning systems, such as learning management systems (LMS) are becoming more common features of today's students' learning experiences, thereby providing a more ubiquitous source of data. Research using trace data is still in early stages and more work is needed to evaluate its potential. The purpose of this dissertation was to further this evaluative work.

The purpose of Articles 2 and 3 was to study the relationship between the data collected from the self-report instrument and user activity data, or log data, collected from the university LMS. Appleton et al. (2006) have argued that self-report is the only valid means for measuring the internal aspects of students' engagement, such as their cognitive or emotional states. However, if log data highly correlates with self-report data, they could be a valuable proxy for measuring student engagement.

In Article 2, we created an activity-level self-report measure of student engagement that included both cognitive and emotional engagement scales. As no activity-level instruments existed, it was necessary for us to create one. An activity-level instrument focuses on in-the-moment experiences as opposed to a longer-term experience, like a semester or year. As log data represent in-the-moment data, it was important for us to have comparable self-report data. We founded our instrument on established course and school-level instruments and revised them to focus on in-the-moment learning experiences. Our model of students' cognitive and emotional engagement fit the data well (RMSEA = 0.050, CFI = 0.985, TLI = 0.971, SRMR = 0.033). We were unable to confirm measurement invariance in the data we collected from different samples. This may have been the effect of a small sample size. Measurement invariance would indicate that survey takers interpret the different points of the instrument scales similarly across samples. This is important for valid comparison of scores across samples. We have not seen this level of evaluation applied to existing student engagement instruments. We were able to confirm our data model across samples, similar to what has been done with other student engagement instruments. While we did not confirm measurement invariance, we were able to meet other standards of scale evaluation, and believe our instrument would be a meaningful measure of student engagement.

In Article 3, we compared students' survey scores to their log data obtained from the LMS. Students used the survey to respond to specific learning activities. The log data matching those activities were extracted from the LMS. We ran correlations between the two data sources for each activity within each course that participated in the study. In the three courses we examined, only one was found to have statistically significant correlations between the survey data and the log data. These correlations were considered moderate at best (highest correlation was 0.377).

In short, we have found LMS log data to not be the strongest proxy measure of students' cognitive and emotional engagement. Our inability to find a strong relationship is likely due to the complex nature of learning. Many other factors could be accounted for in studying the relationship between internal affective and cognitive states and observed behavior, such as students' prior ability, or whether they experienced confusion during learning. Both of these factors would affect how long a student spends on an assignment or how frequently they return to a page. Other types of log data may correlate better with self-reported engagement, such as using mouse tracking data. Other work in comparing log data to affective and cognitive states through other measures (such as human observation or physiological sensors) has been promising, but accuracy in classifying these states still has room for improvement (Baker et al., 2012; D'Mello & Graesser, 2012). This raises questions about how to validly measure students' cognitive and emotional engagement. Future research is needed to investigate these issues to better determine the value of log data as a measure of engagement.

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