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Conceptualizing Blended Learning Engagement

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Doctor of Philosophy

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ABSTRACT

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Learner engagement, or the involvement of the student's cognitive and emotional energy to accomplish a learning task, has been called "the holy grail of learning" (Sinatra, Heddy, & Lombardi, 2015, p. 1) because of its correlations to academic achievement, persistence, and satisfaction. In the 21st century, learning will be increasingly "blended," combining face-to-face with computer-mediated instruction. Research is already exploring learner engagement in blended contexts, but no theoretical framework guides inquiry or practice. Developing models and measures of the factors that facilitate learner engagement is important to the advancement of the domain. This multiple-article format dissertation addresses the theoretical gap in research on learner engagement in blended settings. The first article reviews the existing literature on learner engagement, delineates a set of constructs most relevant to the contexts of blended learning, and proposes a theoretical framework for learner engagement in blended settings. The second article operationalizes and tests the proposed model of blended learning engagement using exploratory and confirmatory factor analysis. It creates and evaluates an end-of-course self-report measure of cognitive and emotional engagement. The unique factor structure of online and face-to-face indicators of learner engagement is clearly demonstrated in the results of this study.

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My husband Taylor Halverson has supported me in countless ways as I've juggled classes, research, teaching, and motherhood. Our children have spent nearly every Saturday for the last several years on adventures with Dad – while Mom stayed home to write. When, six months ago, I lost the hearing in one of my ears, Taylor encouraged me to move forward with the cochlear implant surgery that will help in the long run, but that has required much more time and energy than we expected and necessitated even more support from Taylor. Thank you for always opening doors for me.

Finally, life is rich and exciting because of my two children, David and Rachel. You are my miracles!

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DESCRIPTION OF RESEARCH AGENDA AND STRUCTURE OF THE DISSERTATION

The purpose of this dissertation is to propose, operationalize, and test a theoretical framework for learner engagement in technology-mediated environments. Learner engagement is the investment of mental and emotional energy in the learning process, and its importance to student learning, satisfaction, and persistence has been widely acknowledged (Filak & Sheldon, 2008; Fredricks, Blumenfeld, & Paris, 2004; Hughes, Luo, Kwok, & Loyd, 2008; Kuh, Cruce, Shoup, Kinzie, Gonyear, & Gonyea, 2008; Reschley & Christenson, 2012). As the learning of the 21st century becomes increasingly "blended," combining face-to-face with computer-mediated instruction, understanding the nature of learner engagement in different modalities becomes increasingly important.

Several hurdles to understanding engagement in blended settings exist, including the dynamic and evolving conception of blended learning, the lack of definitional clarity about learner engagement, and the absence of an instrument to measure learners' degree of engagement in blended learning environments. Without such an instrument, it becomes impossible to measure the impact of specific designs or make comparisons across different contexts (Henrie, Halverson, & Graham, 2015), all the more critical because effective and engaging "blending" is not unilaterally conceived or implemented. But instrument creation is hampered by the fact that there does not exist a universally accepted definition for learner engagement (Fredricks, Blumenfeld, & Paris, 2004), let alone blended learning engagement. There is a need for theoretical clarity in the study of learner engagement in blended settings and for research instruments aligned with such theory (Onku & Cakir, 2011).

This multiple-article format dissertation proposes, operationalizes, and tests theoretical models and measures of blended learning engagement. It is written in a hybrid format,

combining traditional dissertation requirements with journal publication formats. The preliminary pages of the dissertation reflect requirements for submission to the university. The dissertation report is presented as a journal article, and conforms to length and style requirements for submitting research reports to education journals. Article 1 is also an extensive review of the literature on learner engagement.

Article 1

In the first article in this dissertation, "Learner Engagement in Blended Learning Environments: A Conceptual Framework," we reviewed the existing literature on learner engagement and found much "duplication of concepts and lack of differentiation in definitions" (Fredricks et al., 2004, p. 65). Across several models of learner engagement, theoretical "jingle and jangle" prevailed, with the same term being used for different things and different terms being used for the same construct (see Reschly & Christenson, 2012). Additionally, facilitators and indicators of engagement are at times indiscriminately grouped. Several key instruments attempt to measure learner engagement at the institutional level, but this may be "a different reality than engagement in the classroom or, even more circumscribed, in learning activities. . . . [T]here may be no necessary equivalence between engagement in school and engagement in specific learning activities" (Janosz, 2012, p. 698). Finally, we found no comprehensive framework established and operationalized to understand engagement in blended contexts.

Unable to find an existing model to apply to the affordances of blended learning, we delved further into the literature in order to propose a theoretical framework for blended learning engagement. We proposed that the most fundamental indicators of engagement were those that demonstrated learner investment of mental and emotional energy in the learning process (see also Astin, 1984; Janosz, 2012; Schunk & Mullen, 2012). Drawing upon the literature of fields

such as educational psychology, human development, and human-computer interaction, we proposed subconstructs for cognitive and emotional engagement that might best apply to the affordances of blended contexts. This paper was not an empirical study but a case for a theoretical model, intended to guide future measurements of engagement, which can test the efficacy of blended interventions and designs.

This article was selected for the *Educational Technology Research and Development* Young Scholar Award in 2015. It was submitted to the journal in October 2015 and has been through one cycle of review and revision.

Article 2

The second article in this dissertation, "Scale Development to Measure Learner Engagement in Blended Learning Environments," operationalized and tested the proposed model of blended learning engagement using exploratory and confirmatory factor analysis. We developed investigated the structural validity of a new end-of-course self-report instrument to measure blended learning engagement. To generate items for our scale, we consulted various related instruments, although very few of the face-to-face items matched our purposes without alteration and all online items had to be created anew.

The instrument, which we called the Blended Learning Course Engagement Survey, accounted for context (online or face-to-face) and the cognitive and emotional aspects of learner engagement. Results indicated that the original model be adjusted to separate factors by context, as the unique factor structure of online and face-to-face indicators of learner engagement is clearly demonstrated. Lack of discriminant validity between first order factors led to a respecification of the original model. Future research can further refine the engagement scale utilized in this research. Contributions that this framework and scale can make to theory and

pedagogy are discussed. *Computers & Education* or *The Internet and Higher Education* are

potential outlets for publishing this article.

Article 1: Learner Engagement in Blended Learning Environments:

A Conceptual Framework

Learner Engagement in Blended Learning Environments:

A Conceptual Framework

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Abstract

Learner engagement correlates with important educational outcomes, including academic achievement, persistence, and satisfaction. In the 21st century, learning will be increasingly "blended," combining face-to-face with computer-mediated instruction. Although research is already exploring learner engagement in blended contexts, no theoretical framework guides inquiry or practice, and there is little consistency or even specificity in the definitions and operationalizations of engagement. Developing definitions, models, and measures of the factors that indicate learner engagement is important to the advancement of the domain. Greater clarity is needed about facilitators versus indicators of engagement in order to establish whether changes in instructional methods (facilitators) have actually resulted in improved engagement (measured via indicators). This article examines existing literature on learner engagement and identifies constructs that are most relevant to learning in general and blended learning in particular. We then propose a theoretical framework for learner engagement that includes both cognitive and emotional indicators and investigates their relevance to blended learning contexts. We share examples of research measuring these engagement indicators in technology-mediated learning contexts. We believe this framework can support advances in blended learning engagement research that is increasingly real-time, minimally intrusive, and maximally generalizable across various subject matter contexts.

Keywords: learner engagement; cognitive engagement; emotional engagement; blended learning; hybrid learning; theory

Introduction

Learner engagement, defined as the involvement of the student's cognitive and emotional

energy (Astin, 1984; Schunk & Mullen, 2012) to accomplish a learning task, has been found to

correlate with important educational outcomes, including academic achievement (Hughes, Luo,

Kwok, & Loyd, 2008; Ladd & Dinella, 2009; Nystrand & Gamoran, 1991), satisfaction (Filak &

Sheldon, 2008; Zimmerman & Kitsantas, 1997), sense of community (Conrad, 2010; Robinson,

2010), and persistence (Berger & Milem, 1999; Kuh et al,, 2008). Such correlations have

prompted scholars to refer to learner engagement as "an educational bottom line" (Coates, 2006,

p. 36) and "the holy grail of learning" (Sinatra, Heddy, & Lombardi, 2015, p. 1). Yet many

students today are not engaged in their own education, resulting in high attrition as well as low

interest, motivation, and academic outcomes (Chapman, Laird, & Kewalramani, 2011;

Rumberger & Rotermund, 2012).

Many educators have hoped that blended learning (BL), which is the thoughtful

integration of face-to-face and online instruction, can more fully engage students in their learning

(Aspden & Helm, 2004; Graham & Robison, 2007). BL may support improved reflection and

critical discourse (Garrison & Kanuka, 2004), important in cognitive engagement (CE) (Nystrand

& Gamoran, 1991). Technology-mediated instruction can offer multiple pathways for studying a

particular topic, increasing choice and thus assisting agentic engagement (Reeve & Tseng, 2011).

Emotional engagement (EE) may be preserved and enhanced through the face-to-face interactions

in BL, though this idea needs further research. Nelson Laird and Kuh (2005) found a strong

positive relationship between use of information technology for educational purposes and

indicators of engagement as per the National Survey of Student Engagement (NSSE). Interest in

learner engagement is high among BL proponents, with almost half of the top-cited publications

on BL employing the term *engagement* (Halverson, Graham, Spring, & Drysdale, 2012). Yet only four of the 85 top-cited articles and chapters addressed the topic in their research questions (Halverson, Graham, Spring, Drysdale, & Henrie, 2014). Even though scholars and practitioners show interest in the potential of BL to increase learner engagement, more research is essential.

Several hurdles to researching engagement in blended settings exist, including the dynamic and evolving conception of BL, the lack of definitional clarity about learner engagement, and the confusion between facilitators and indicators of engagement. The first obstacle is the nature of BL itself. At the most basic level, BL involves the combination of face-to-face and technology-mediated (or online) instruction (Graham, 2013). However, BL is a high level term that is often defined in terms of its surface features (online and face-to-face) rather than its pedagogical features (Graham, Henrie, & Gibbons, 2014). Some authors (Graham, 2013; Laumakis, Graham, & Dziuban, 2009; Norberg, Dziuban, & Moskal, 2011) have referred to the term as a boundary object, "plastic enough to adapt to local needs and constraints of the several parties employing them, yet robust enough to maintain a common identity across sites" (Star & Griesemer, 1989, p. 393). Some are frustrated by this lack of specificity, while others see a flexibility that allows "individual institutions and collaborative groups to tailor the concept to maximize its potential while being responsive to a new generation of students" (Moskal, Dziuban, & Hartman, 2012, p. 16). Accordingly, engaging and effective blending can involve countless possible combinations of human- and technology-mediated instruction—neither conceived nor implemented unilaterally. Research is needed to clarify which blended designs most effectively increase learner engagement and thus student learning.

To measure changes in learner engagement, greater theoretical and definitional clarity about engagement is required. At present, no definition for learner engagement is universally

accepted. Literature on the topic has been described in terms of "duplication of concepts and lack

of differentiation in definitions" (Fredricks, Blumenfeld, & Paris, 2004, p. 65). If research on

learner engagement is theoretically entangled, it is no surprise that learner engagement in blended

settings is still a theoretically undefined and untested domain. Henrie, Halverson, and Graham

(2015) found little consistency or even specificity in the definitions and operationalization of

engagement in literature measuring engagement in technology-mediated learning (TML). This

paper reviews the existing literature on learner engagement and proposes a definition and set of

theoretical constructs for learner engagement in blended settings. This theoretical framework is

intended to provide guidance to researchers interested in measuring learner engagement in

blended contexts.

A final challenge in researching engagement is the not infrequent confusion of *facilitators*

and *indicators* of engagement. According to Skinner, Furrer, Marchand, and Kindermann (2008),

"Indicators refer to the features that belong inside the construct of engagement proper, whereas

facilitators are the causal factors (outside of the construct) that are hypothesized to influence

engagement" (p. 766). When BL advocates speak of best practices or optimal blends, they are

proposing the contextual facilitators that will encourage engagement and thus student learning.

But we cannot evaluate the effect of those proposed interventions until we have a clear set of

engagement indicators to measure. Several existing instruments to measure engagement actually

mix facilitators and indicators. For example, the recently revised NSSE lists ten *engagement*

indicators, but many of these (especially those in the Effective Teaching Practices category)

assess practices that facilitate engagement, not the indicators that engagement is occurring.

In this paper we propose a cohesive set of engagement indicators that are applicable to the

contexts of both face-to-face and technology-mediated instruction. We have drawn these

indicators from the literature of fields such as educational psychology, human development, and human-computer interaction, trying to find the configuration of constructs that would best apply to learner engagement in BL contexts. Although our research team is currently using factor analysis to test the model with empirical data, this paper is not an empirical study but a case for a theoretical model. However, we hope our framework will guide future measurements of engagement, testing the efficacy of blended interventions and designs and better determining which facilitators most efficaciously improve engagement.

Literature Review

Terms like *learner engagement* or *student engagement* are used prolifically, even excessively, in educational research. Azevedo (2015) reported that a search on PsycINFO unearthed more than 32,000 articles about engagement dated over the last 14 years. Because standard keyword database searching gave us much that was irrelevant or used *engagement* too loosely for our purposes, we began our literature review with the 50-page overview of school engagement by Fredricks et al. (2004). This highly cited paper reviewed definitions, measures, facilitators, and outcomes of engagement. Its appendix compiled 44 studies that used the term *engagement*, listing definitions, measures, methods, and key findings. More recently, Fredricks, McColskey, Meli, Mordica, Montrosse, and Mooney (2011) published an expansive report on how engagement was measured in K-12 settings. We looked up each study and instrument, as well as other referenced literature. Each retrieval led to new references, and we gradually gathered more than 900 articles, chapters, and instruments on engagement. Then to ensure that no influential works on learner engagement had slipped by, we reviewed the results from Harzing's (2014) Publish or Perish software, which calculates academic citations from Google Scholar, using a title search of the 100 top-cited results for *engagement*. From these we gleaned

additional relevant publications to review. We also used Publish or Perish to search for *learner engagement* and *student engagement*, adding relevant publications found.

Another extensive resource in the literature on learner engagement is the recently published *Handbook of Research on Student Engagement* (Christenson, Reschly, & Wylie, 2012), incorporating 39 chapters on learner engagement. Each contributor to this 839-page volume was asked to consider: *What is your definition of engagement?* and *What overarching framework or theory do you use to study/explain engagement?* (p. vii). The diverse contributions showed, as Fredricks et al. (2004) had warned, that research still seeks a consensus on the definitions, frameworks, and constructs of engagement. The tome's opening chapter (Reschly & Christenson, 2012) is titled "Jingle, Jangle, and Conceptual Haziness": in psychology, *jingle* refers to the same term being used for different things and *jangle* designates different terms being used for the same construct (see Kelly, 1927; Thorndike, 1913). Reschly and Christenson displayed a table comparing four prominent engagement models on key dimensions such as number of types or subconstructs and definitions or indicators; we have compiled a similar but expanded table (Table 1). As these demonstrate, a plethora of constructs have been proposed for engagement research and theory.

Table 1

Comparisons of Several Engagement Models on Key Dimensions

Source	No. of types	Indicators of engagement
Appleton & colleagues[a]	4	*Academic*: Time on task, credit accrual, homework completion *Behavioral:* Attendance, in-class and extracurricular participation *Cognitive:* Value/relevance, self-regulation, goal setting, strategizing *Affective/psychological:* Belonging, identification, school membership
Bangert-Drowns & Pyke (2001)	7	*Disengagement*: Avoidance or premature discontinued use *Unsystematic engagement:* Unclear goals *Frustrated engagement*: Inability to accomplish goals *Structure-dependent engagement*: Pursuit of goals communicated by software *Self-regulated interest:* Creates personal goals, makes interesting to self *Critical engagement:* Tests personal understandings, limits of the software *Literate thinking:* Interprets software from multiple, personally meaningful perspectives
Finn (1989)	2	*Participation:* Task-oriented interaction; on-task behaviors; responding to requirements, expenditure of extra time on work *Identification:* Belonging and valuing success in school-relevant goals
Fredricks, Blumenfeld, Friedel, & Paris (2005)	3	*Behavioral:* Participation, positive conduct; involvement in academic, social, or extracurricular activities *Cognitive:* Investment, thoughtfulness, and willingness to exert effort *Emotional:* Appeal; affective reactions to teachers and classmates, academics and school (boredom, interest, anxiety, etc.); belonging; valuing
Handelsman, Briggs, Sullivan, & Towler (2005)	4	*Skills engagement*: Skills practice, general learning strategies *Emotional engagement*: Emotional involvement with the class material *Participation/ interaction engagement*: Participation in class, interactions with instructors and classmates *Performance engagement*: Levels of performance in class, including confidence, performance goals, and extrinsic motivation
High School Survey of Student Engagement[b]	3	*Cognitive/intellectual/academic engagement*: "Engagement of the mind"—effort, investment in work, and strategies for learning *Emotional engagement*: "Engagement of the heart"—students' feelings of connection to (or disconnection from) their school *Social/behavioral/participatory engagement*: "Engagement in life of the school" —actions, interactions, and participation within school community
Martin (2007)	4 higher order factors, 11 subconstructs	*Adaptive cognition:* Valuing, mastery orientation, self-efficacy *Adaptive behavior:* Persistence, planning, study management *Maladaptive behavior:* Disengagement, self-handicapping *Impeding/maladaptive cognition:* Uncertain control, failure avoidance, anxiety
Miller, Greene, Montalvo, Ravindran, & Nichols (1996)	1 higher order factor with 4 subconstructs	*Cognitive engagement:* Self-regulation, cognitive strategy use (deep vs shallow), effort, and persistence
National Survey of Student Engagement[c]	4 "themes" with 10 "engagement indicators"	*Academic Challenge:* Higher-order learning, reflective & integrative learning, learning strategies, quantitative reasoning *Learning with Peers:* Collaborative learning, discussions with diverse others *Experiences with Faculty:* Student-faculty interaction, effective teaching practices

		Campus Environment: Quality of interactions, supportive environment
Pekrun & Linnenbrink-Garcia (2012)	1 + 5	*Emotional:* Considered the antecedent of other components of engagement *Cognitive:* Attention, memory processes *Motivational:* Intrinsic and extrinsic motivation, achievement goals *Behavioral:* Effort, persistence *Cognitive-behavioral:* Strategy use and self-regulation *Social-behavioral:* Social on-task behavior
Reeve & colleagues[d]	4	*Agentic:* Constructive contribution into flow of instruction *Behavioral:* Task involvement, effort, attention *Cognitive:* Metacognitive strategy use, self-regulation, personal application and relevance *Emotional:* Enjoyment, interest, curiosity
Skinner & colleagues[e]	4	*Engagement* • *Behavioral:* Action initiation, effort, hard work, persistence, intensity, attention, absorption, involvement • *Emotional:* Enthusiasm, interest, enjoyment, satisfaction, pride, vitality, zest *Disaffection* • *Behavioral:* Passivity, giving up, withdrawal, restlessness, inattentiveness, distraction, mental disengagement, burn-out, lack of preparation • *Emotional:* Boredom, disinterest, frustration/anger, sadness, worry/anxiety, shame, self-blame

[a] Appleton, Christenson, Kim, & Reschly (2006); Appleton (2012). [b] Yazzie-Mintz (2010).
[c] McCormick, Gonyea, & Kinzie (2013). [d] Reeve & Tseng (2011); Reeve (2012); Reeve (2013)
[e] Skinner, Kindermann, Connell, & Wellborn (2009); Skinner, Kindermann, & Furrer (2009);
Skinner & Pitzer (2012).

Initially we hoped to find an existing model to modify to the affordances of BL. Fredricks et al.'s (2004) comprehensive review of engagement has led many researchers to adopt their tripartite model of emotional, cognitive, and behavioral engagement. However, we (like Fredricks. Blumenfeld, Friedel, & Paris, 2005) noticed overlapping elements for cognitive and behavioral engagement in this and other models. Skinner and colleagues have been gathering data for their model of emotional and behavioral engagement and disaffection since the 1990s (e.g., Skinner & Belmont, 1993), and have some of the clearest explications of indicators versus facilitators of engagement; this combination of clarity and substance was attractive to us. But the absence of a cognitive measurement left vital aspects of learner engagement unexamined. Reeve and colleagues (Reeve, 2012; Reeve & Tseng, 2011) started with Skinner's model and added CE items from other research as well as their own agentic engagement items.

Even if agreement had been reached on construct labels, careful study of the construct descriptions produced additional jingle and jangle. For example, *absorption* is considered by some to be an aspect of CE, by others to be part of behavioral engagement; *valuing* indicates EE in one model and CE in another (Christenson, Reschly, & Wylie, 2012; Fredricks et al., 2011). *Persistence* is a component of CE for Miller, Greene, Montalvo, Ravindran, and Nichols (1996), but of behavioral engagement in the frameworks of Fredricks et al. (2004), Pekrun and Linnenbrink-Garcia (2012), and Skinner and colleagues. Henrie et al. (2015) found particular conceptual fuzziness between cognitive and behavioral engagement; some research stated the intent to measure CE but operationalized the construct in ways other models deemed behavioral.

When we examined engagement definitions, we found additional confusion. While some literature included explicit definitions about engagement, other research jumped straight to its operationalization (see Table 1 in Appleton, Christenson, & Furlong, 2008). Jimerson, Campos,

and Greif (2003) examined 45 articles on engagement and found that 31 did not explicitly define terms. In the narrower context of TML, Henrie et al. (2015) likewise found that the majority of articles reviewed did not clearly define engagement. They wrote, "The future success of research relating subconstructs of engagement to specific outcomes relies on consensus of definitions and measures of engagement" (p. 37). Findings from two studies on engagement may conflict simply because of differences in definition or construct conceptualization.

Even without these shortcomings, transfer of current instruments for measuring learner engagement to blended settings may be questionable. Some researchers have applied existing instruments to technology-mediated settings. For example, to measure engagement in online college students, Sun and Rueda (2012) used Fredricks et al.'s (2005) K-12 classroom engagement scale. To measure engagement in game-based learning, Rowe, Shores, Mott, Lester, and Carolina (2011) combined the Positive and Negative Affect Schedule (Watson, Clark, & Tellegen, 1998) and the Presence Questionnaire (Witmer & Singer, 1998). But overall, existing engagement instruments have numerous items that transfer poorly to blended contexts, requiring revalidation of any instrument adapted to BL.

Thus no comprehensive framework has been established and operationalized to understand engagement in blended contexts. Bangert-Drowns and Pyke (2001) observed students working in a blended setting, then proposed a 7-level taxonomy of engagement with educational software (including simulations, activities, tools, game, tutorials, and internet). Yet no discussion of the blended nature of their engagement constructs was included. O'Brien and Toms (2008) created a list of engagement attributes to predict engaging user-computer experiences. Unfortunately, their compilation mixes facilitators and indicators of engagement, as well as characteristics of the computer application and the participant: challenge, positive affect,

endurability, aesthetic and sensory appeal, attention, feedback, variety/novelty, interactivity, and

perceived user control. Coates (2007) applied the Student Engagement Questionnaire (SEQ) to

online as well as more "general campus-based engagement" (p. 121) but narrowly limited online

learning to use of learning management systems (LMS).

Another limitation is that the SEQ, like the widely used NSSE (Kuh, 2009; NSSE, 2014)

and Student Engagement Instrument (Appleton, Christenson, Kim, & Reschly, 2006), focuses

primarily on institutional level engagement (Skinner & Pitzer, 2012). Institutional engagement

promotes retention and discourages dropout—vital educational goals. But improving BL design

requires understanding when students are engaging with their learning and when they begin to

disengage. To do this, engagement must be conceptualized and then measured at the course and

activity levels—termed the *microprocess level* (Ainley, 2012) and *grain sizes* (Sinatra, Heddy, &

Lombardi, 2015). We feel that "[e]ngagement should be measured at the same specificity level as

the intervention" (Wang, Bergin, & Bergin, 2014, p. 518). Indeed, engagement at the institutional

or school level is "a different reality than engagement in the classroom or, even more

circumscribed, in learning activities. . . . [T]here may be no necessary equivalence between

engagement in school and engagement in specific learning activities" (Janosz, 2012, p.

698). Thus models and scales which focus on the institutional level can tell us little about

measuring engagement in specific BL courses and activities. If "engagement is fundamentally

situational" (Kahu, 2013, p. 763) and "occurs during the actual experience of an activity or event"

(Davis & McPartland, 2012, p. 516), then by understanding how engagement fluctuates in

different face-to-face and online situations we can improve the design of BL.

But merely collecting class- and activity-level case studies of learner engagement will not

give us the "reasonably stable theory base . . . [that] allows for a clear focus on important issues

and provides sound (though still limited) guidance for the design of improved solutions to important problems" (Burkhardt & Schoenfeld, 2003, p. 6). We need a theoretical framework to guide research into learner engagement in settings that combine face-to-face with computer-mediated instruction. As Meyer (2014) noted regarding online learning,

> It is not sufficient to rely on the research conducted in the pre-Internet era to claim that pursuing student engagement has an effect on positive outcomes of interest to institutions and students; instructors and designers involved in online learning must prove such an effect for online learning specifically. (p. 72)

Current engagement models and instruments are inadequate due to contextual affordances (course and activity level vs. institutional) and to conflation of constructs and subconstructs of engagement. A new model of learner engagement is needed to guide research in BL settings.

Formation of the Learner Engagement Model

Given this landscape littered with overlapping or conflicting definitions and constructs of engagement, and instruments not adapted to blended contexts, we decided to establish a theoretical framework of engagement, applicable to engagement in general but also suited to inform the creation of instruments to measure engagement in both face-to-face and technology-mediated contexts. Our overall logic model (see Figure 1) encapsulates both facilitators and indicators of engagement, but our intent in this paper will be to establish which indicators, culled from the literature, are most fundamental to understanding engagement. Once these are clearly established, then BL research can test various designs and interventions, manipulating various facilitators and assessing their effect upon engagement.

Thus we begin by inquiring into the most fundamental expressions of learner engagement. Janosz (2012) stated, "To develop new skills and acquire new knowledge,

individuals must consciously mobilize and devote some of their physical and psychological (cognitive, emotional) energy; they must *engage* themselves in the learning situation" (p. 695). We propose that the most elemental indicators of engagement show whether learners are investing mental and emotional energy in the learning process. Research acknowledges the primacy of emotional and cognitive engagement. Reschly and Christenson (2012) classified cognitive and affective engagement as individual internal processes that mediate and precede academic and behavioral engagement. Appleton et al. (2006) proposed moving beyond academic and behavioral indicators to focus on "the underlying cognitive and psychological needs of students" (p. 430). Research from human-computer interaction and educational data mining measure this energy by examining what they call "cognitive-affective states" (Baker, D'Mello, Rodrigo, & Graesser, 2010; D'Mello & Graesser, 2011).

In a domain that has sometimes (erroneously in our view) emphasized seat-time over pedagogy in its definition of blending (Picciano, 2009), a focus on cognitive and emotional engagement reminds us that internal processes are paramount. Still some may be surprised that our model does not include behavioral engagement as a key indicator. Henrie et al. (2015), reviewing measures of student engagement in TML, found that 77% of the research measured behavioral indicators, while only 43% measured cognitive and 41% emotional indicators. Engagement research that uses educational data mining techniques may measure online behaviors such as click data, assignment submission, or time viewing videos (Kizilcec, Piech, & Schneider, 2013; Ramesh, Goldwater, Huang, Daum, & Getoor, 2013), hoping those behaviors imply emotional and cognitive engagement. We argue that what other models are considering displays of behavioral engagement are actually indicators of underlying cognitive and emotional involvement. Renninger and Bachrach (2015) suggested that the ability of a learner to

behaviorally engage without emotional and cognitive investment implies that behavior should be

considered separately. Piaget (1981) argued that all behavior has cognitive and affective

underpinnings, with affectivity providing energy to intellection. Thus researchers may infer

internal processes from external behaviors; these behaviors are not trivial, but must be recognized

as outward displays of the mental and emotional energies that fuel learning.
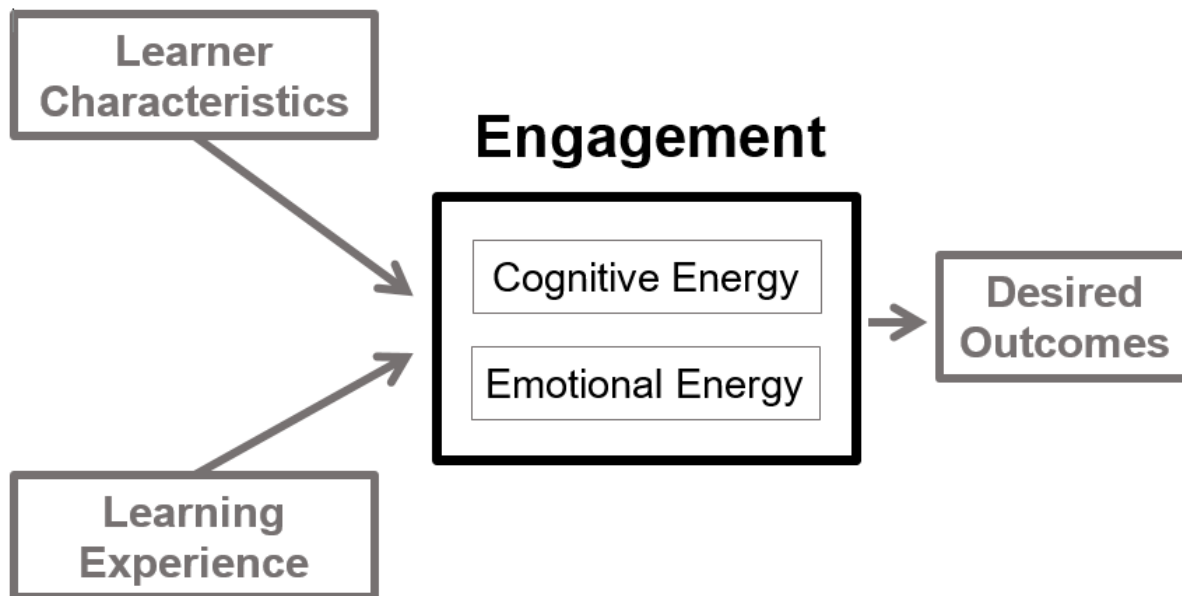
Figure 1. Overall logic model of relationship between learner characteristics, learning
experience, engagement, and outcomes.

Consequently, this framework proposes that CE and EE are the key factors essential to

understanding learner engagement. Figure 1 displays our overall model of the relationship of

learner characteristics, learning experience, engagement, and desired learning

outcomes. Personal and contextual *facilitators* of engagement, including learner characteristics

and thoughtful learning experience design, can increase the likelihood of learner

engagement. Engagement is manifest via cognitive and emotional *indicators* and contributes to

desired learning outcomes.   We have crossed disciplines to cull the first order factors proposed to

indicate cognitive and emotional engagement, forging a more unified framework that can be acceptably operationalized in both face-to-face and technology-mediated contexts. As we discuss these indicators, we will not attempt to propose every BL practice that might lead to them—research on BL facilitators must fill in this gap. Since we are focusing on indicators, we will offer some examples of how such indicators have been measured in blended contexts.

Cognitive Engagement

Cognitive engagement—the expenditure and reception of mental energy—has long been the subject of theoretical debate (Pintrich & DeGroot, 1990; Zimmerman, 2002). Our framework proposes that CE is comprised of several first order factors, some of which indicate the quantity of CE, others the quality (see Figure 2).
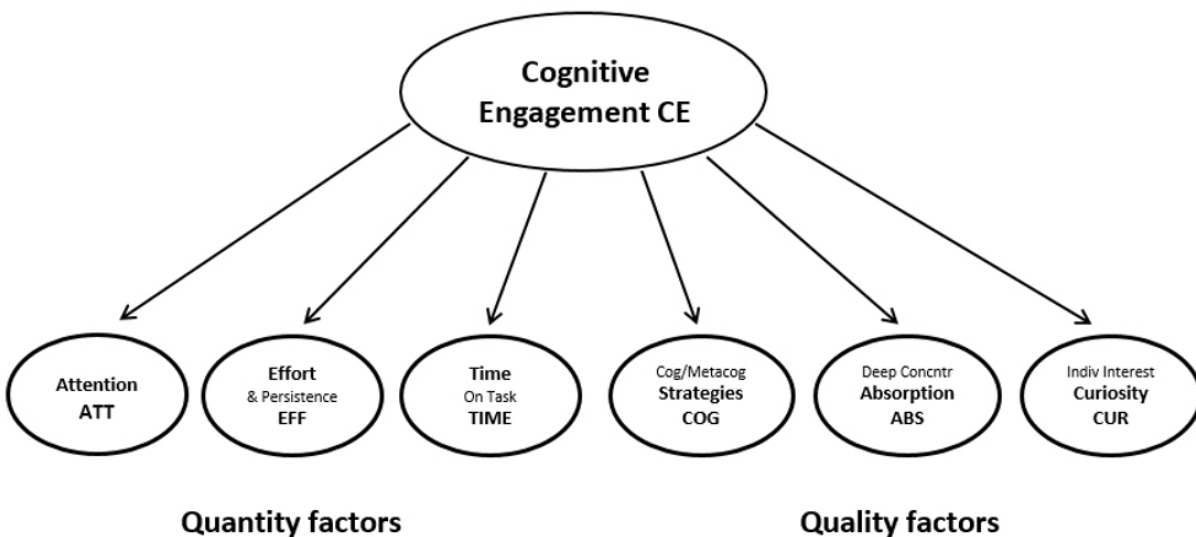
Figure 2. Model of CE. Attention, effort and persistence, and time on task indicate the *quantity* of CE, while cognitive strategy use, absorption, and curiosity indicate its *quality*.

Factors indicating quantity of CE. Our first three factors include the more outwardly visible and quantifiable indicators that mental energy is being put toward learning: attention, effort and persistence, and time on task. In the literature these variables were labeled *behavioral*

in some frameworks and *cognitive* in others (Henrie et al., 2015). Pekrun and Linnenbrick-Garcia's (2012) model shows the overlap: Cognitive, behavioral, and cognitive-behavioral are among their five types of engagement. Proponents of divergent perspectives may question our labeling of these indicators as cognitive rather than behavioral. Certainly the variables that we incorporate here may include behaviors, yet we consider them behaviors reflecting the presence or absence of mental energy focused on learning. Moreover, when we collected formative feedback on an early version of an instrument based on this framework, giving an end-of-course engagement survey to students (*n*=57) in a blended course, exploratory factor analysis showed that both quantity and quality factors loaded well onto one higher-level factor—cognitive engagement. We hypothesize that subsequent empirical studies will find that these factors converge, together reflecting the expenditure and reception of mental energy.

Some consider *attention* the defining attribute of engagement (e.g., Cocea & Weibelzahl, 2011). Miller (2015), using self-paced reading and eye-tracking methodologies to measure engagement, called attention "the baseline of engagement" (p. 34). Keller's (1987, 2008) ARCS model of motivational design established attention as the first stepping-stone to other means of motivating learners (relevance, confidence, and satisfaction follow). Attention is a cognitive process, as are perception, deliberation, and memory (Calvo & D'Mello, 2010; Lehman, D'Mello, & Graesser, 2012); Pekrun and Linnenbrick-Garcia (2012) included attention and memory processes in conceptualizing CE. Attention is the gatekeeper for information processing (Atkinson & Shiffrin, 1968); without it, learning could not take place. Attention is one of the most basic indicators that learners are engaging mental effort in the learning process.

Some have measured attention using classroom observation, but online aspects of a blended course may be at a distance, making such techniques impractical. Other methods for

measuring attention during online instruction track eye movement (Boucheix, Lowe, Putri, & Groff, 2013; Miller, 2015; Toyama, Sonntag, Orlosky, & Kiyokawa, 2015), brainwaves (Sun, 2013), or gross body language (D'Mello et al., 2008). Already intelligent tutoring systems (ITSs) attempt to reengage students when they perceive waning attention (D'Mello et al., 2008), and as understanding of blended and online learner engagement improves, additional data-rich systems will sense waning attention and provide real-time feedback to both learner and instructor (Bienkowski, Feng, & Means, 2012).

Effort and persistence and *time on task* are dimensions of CE that manifest in outward behaviors but, of more importance, reflect expenditure of mental energy towards learning. Any researcher who has tried to differentiate between time logged on an LMS and actual time on task characterized by effort and persistence would intuitively understand the interest in CE, not just behavior: as in face-to-face learning, time spent on task is desirable primarily when accompanied by cognitive effort and committed persistence. Thus Miller et al. (1996) saw effort and persistence as variables that indicated cognitive engagement, and found both to be significantly related to academic achievement.

Persistence counteracts the likelihood of attrition, which may be higher in online than in traditional settings (Carr, 2000; Diaz, 2002). In addition to course-level measures of persistence (often, did the student complete the course), Tan, Sun, and Khoo (2014) employed activity-level measures of persistence. They used log data from the online ASSISTments Math Tutor program to map engagement levels to engagement indicators. "Persistency" was operationalized as revisiting and spending extra time on difficult tasks, using hints appropriately, and completing all tasks on time. Persistence occupied the fourth of five hierarchical levels, just lower than enthusiasm, in importance to learning.

The link between academic engaged time and learning "is one of the most enduring and consistent findings in educational research" (Gettinger & Walters, 2012, p. 654), such that some researchers have argued that *time on task* is the single most influential factor in student success (Farragher & Yore, 1997). Time on task has been ranked "most reflective of the degree of student engagement in classroom learning" (Kong, 2011, p. 1856). Nevertheless, in blended and online contexts, conceptualizing and measuring time on task can be complex. Beck (2004), studying learner interaction with computer tutors, considered time on task the most basic component of engagement, yet his model fit best when he incorporated question difficulty and response accuracy. Macfayden and Dawson (2010), mining log data to measure engagement in online courses, found that other measures of engagement—interaction with peers through discussion forums, number of optional self-test quizzes completed, and attention to administrative details—were more important than time online. Cocea and Weibelzahl (2011) also examined log data and found the most valuable factor for detecting disengagement to be the average time spent on content pages: spending too little *or* too much time on a page could indicate disengagement.

Care must be taken if time-on-task data are drawn from diverse blended courses. Many blended courses replace seat time with online expectations (Picciano, 2009), but some instructors may consider the face-to-face activities as optional enhancement, not required work. In BL contexts, measuring time on task in face-to-face and online settings must account for policies of seat-time flexibility.

Factors indicating quality of CE. CE also comprises factors indicative of the *quality* of engagement, namely cognitive and metacognitive strategy use, deep concentration or absorption, and individual interest or curiosity. These factors are supported by one of the most frequently employed theories in BL research (Halverson, et al., 2014), Garrison, Anderson, and Archer's

(2001) Community of Inquiry framework. The framework proposes that the requirements for

effective online educational transaction include cognitive presence, which is further broken down

into triggering events (which pique curiosity), exploration, integration (cognitive and

metacognitive strategies applied to solidify understanding), and resolution.

Many existing descriptions of CE focus either on effort and persistence or on *cognitive

and metacognitive strategies*. Winne and Baker (2013) proposed that with metacognitive

monitoring and control, learners are "actively engag[ing] in thinking about their learning" (p. 3),

expending mental energy in the process of learning. Reeve (2012, 2013) stated that cognitive

learning strategies were the better indicators of CE, since metacognitive strategy use cross-loaded

with behavioral engagement (Reeve & Tseng, 2011). This might be another reason for

interpreting behavioral engagement as an outward manifestation of the more fundamental

constructs of CE and EE.

In blended and online contexts, cognitive and metacognitive strategy use and the closely

correlated ability of self-regulation (Sun & Rueda, 2012) may be particularly important. Meyer

(2014) wrote, "Learning self-regulation is especially important in online learning [where being

successful] . . . depends upon the student's discipline, self-direction, and ability to remain

motivated" (p. 24). At the same time, hypermedia use (common in blended and online resources)

"greatly increases task demands and requires the learner to stretch limited processing resources

across two major constraints: to-be-learned information and the hypermedia environment"

(Schraw, 2010, p. 258). Fortunately, online tasks also give us new ways to measure cognitive and

metacognitive strategy use and self-regulation: Winne and Baker (2013) proposed using

educational data mining techniques to provide real-time data about these factors and about the

process of learning "as it unfolds" (p. 1).

Another first order factor that indicates the quality of focused mental energy in learning is *deep concentration or absorption*. Early conceptualizations of absorption defined it as a trait or disposition (see Tellegen & Atkinson, 1974). Later research distinguished ways in which absorption functions as a state to which individual or situational factors lead (Agarwal & Karahanna, 2000). Absorption may express a deep level of attention (Keller, 2008), but is qualitatively different: "paying attention" may be associated with coercion, whereas absorption is a "state in which people are so involved in an activity that nothing else seems to matter" (Csikszentmihalyi, 1990, p. 4). Csikszentmihalyi's theory of flow describes "states of intense concentration or absolute absorption in an activity" (Shernoff, Csikszentmihalyi, Schneider, & Shernoff, 2003, p. 161) accompanied by a sense of control, exhilaration, and deep happiness; in such cases mental energy is not only being expended but also created. Researchers have applied the flow theory to studies of human-computer interaction (Agarwal & Karahanna, 2000; Hoffman & Novak, 1996; Trevino & Webster, 1992). Ghani and Deshpande (1994), studying computer use in the workplace, evaluated enjoyment and total absorption; Estenban-Millat, Martínez-López, Huertas-García, Meseguer, and Rodríguez-Ardura (2014) proposed a model of flow in online learning environments and found that focused attention (similar to our conception of absorption) was one of the two most important direct determinants of a state of flow.

Our final first order variable of CE, *individual interest or curiosity*, must be distinguished from the short-lived emotional experience of situational interest (Ainley, 2012; Hidi & Renninger, 2006). According to Senko and Miles (2008), the latter "refers to enjoyment of external stimuli, such as an entertaining lecture or catchy story" (p. 567); we propose that situational interest and enjoyment are part of positive EE, to be discussed shortly. When the learner perceives the material to be personally relevant, "situational interest may develop into

individual interest, which is characterized by curiosity and self-guided exploration" (p. 567; see also Dewey, 1910). Interest research portrays cognitive and affective components as co-occurring (Hidi & Renninger, 2006; Renninger & Bachrach, 2015), but prioritizes emotion in triggering situational interest, whereas cognitive processes such as stored learning and curiosity have primacy in individual interest.

We will focus on *cognitive curiosity* (Reio, Petrosko, Wiswell, & Thongsukmag, 2006), also termed *scientific* (James, 1890/1950), *epistemic* (Berlyne, 1978), or *intellectual curiosity* (Dewey, 1910); we will not explore physical, social (Dewey, 1910), perceptual (Berlyne, 1978), sensory (James, 1890/1950), or other curiosity variants (Reio et al., 2006). Cognitive curiosity is a "deeper level of attention" stimulated by the learner's sense of inquiry (Keller, 2008, p. 177). Berlyne (1978) posited that curiosity, resulting from subjective uncertainty, may generate "exploratory behavior aimed at resolving or partially mitigating the uncertainty" (p. 98). This exploration is one way that mental energy is expended in learning.

Some have argued that computer use can abet curiosity as the learner explores, experiments, and browses (Ghani & Deshpande, 1994), though such behaviors, if labeled "surfing the web," may be discouraged in educational contexts. Technology-pervasive learning environments may even alter how curiosity is expressed and sustained (Arnone, Small, Chauncey, & McKenna, 2011). Curiosity is among the discrete cognitive-affective states frequently present in TML (D'Mello, 2013), and the studies included in that meta-analysis demonstrate new ways to measure curiosity in TML, such as using multichannel physiological signals to gauge learner reactions to ITSs (Pour, Hussein, AlZoubi, D'Mello, & Calvo, 2010; Hussein, AlZoubi, Calvo, & D'Mello, 2011) or prompting frequent self-report via smartphone in game-based learning environments (Sabourin, Mott, & Lester, 2011).

We believe that the affordances of BL have the potential to encourage CE, an energy indicated by attention, effort and persistence, time on task, cognitive strategy use, absorption, and curiosity. BL may diversify the learning pathways available to accomplish a task; this increased flexibility and personalization abets curiosity, absorption, and attention (Estenban-Millat et al., 2014). At the same time, personalization and flexibility may require learners to employ greater effort and cognitive strategy use. When time on task is accompanied by effort (even absorption), deep learning occurs. At the same time, BL preserves the benefits of humanness (Graham, 2006), which encourage CE while mediating the varied emotions that inevitably arise during learning.

Emotional Engagement

Picard, who coined the term *affective learning*, has noted "an accelerated flow of findings in multiple disciplines supporting a view of affect as complexly intertwined with cognition in guiding rational behaviour, memory retrieval, decision-making, creativity, and more" (Picard et al., 2004, p. 253). Pekrun (2011) argued that emotions 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) labeled emotion "the fuel for the kind of behavioral and cognitive engagement that leads to high-quality learning" (p. 33). The intertwining of mental and emotional energy is also acknowledged in human-computer interaction research of "cognitive-affective states" (Baker et al., 2010; D'Mello & Graesser, 2011).

Even as consensus coalesces around the importance of emotions in learning, the emotions to be studied—particularly in TML—are still up to debate. According to Picard et al. (2004), "[T]here is still very little understanding as to which emotions are most important in learning, and how they influence learning. To date there is no comprehensive, empirically validated, theory of emotion that addresses learning" (p. 255; see also Lopatovska & Arapakis, 2011). Research from

the fields of human-computer interaction, artificial intelligence, and computer science has found

that the prominent emotions occurring during complex learning with technology are different

from Ekman's (1992) basic universal emotions: anger, disgust, fear, joy, sadness, and surprise

(Graesser & D'Mello, 2011). D'Mello (2013) performed a meta-analysis tracking 17 affective

states across 24 studies; he found the discrete states most frequent in TML to be boredom,

engagement/flow, confusion, curiosity, happiness, and frustration. We include these cognitive-

affective states in our EE constructs, considering curiosity part of CE.

     We also use the work of Skinner and colleagues (e.g., Skinner et al., 2008; Skinner,

Kindermann, & Furrer, 2009). Drawing on motivation theory, they divided EE into two

constructs: emotional engagement and emotional disaffection. We call the comparable constructs

positive EE (POS) and *negative EE* (NEG; see Figure 3).

Emotional Engagement EE
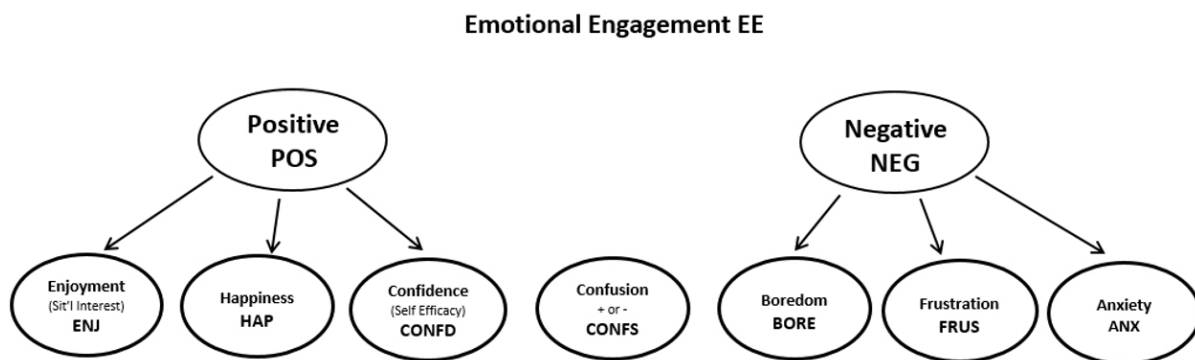
Figure 3. Models of EE (Positive and Negative). The factor of Confusion is unattached for now, for confusion affects engagement and learning differently depending on contextual details.

Positive EE (POS). Research has noted how positive emotions assist learning by

broadening the scope of action, attention, and cognition, and by helping learners "to see

relatedness and interconnections . . . and to process material in a more integrated and flexible

fashion" (Fredrickson, 1998, p. 308; see also Hazlett & Benedek, 2007). We propose that

particular emotions indicate learner engagement. Skinner and colleagues do not differentiate the

positive aspects of EE but focus primarily on interest or enjoyment. Representative items from

their scale include "Class is fun" and "When we work on something in class, I feel interested"

(Skinner, et al., 2008, p. 781). Despite Patrick, Skinner, and Connell's (1993) finding that various

positive emotional items were accounted for by a single factor ($\alpha = .88$), we will investigate

whether additional positive emotions described in other research might indicate the expenditure

and reception of emotional energy in the learning process. We propose that POS includes not

only the first order factor of situational interest (Senko & Miles, 2008) or enjoyment (Skinner et

al., 2008), but also happiness (D'Mello, 2013) and confidence (Arroyo, Cooper, Burleson, Woolf,

Muldner, & Christopherson, 2009; Keller, 2008). We explain these subconstructs below.

As stated, many conceptualizations of EE focus on *enjoyment or situational interest*

(Milne & Otieno, 2007; Furlong et al., 2003). Situational interest, or enjoyment created by

external stimuli (Hidi, 1990; Senko & Miles, 2008), is a short-lived affective state that indicates

emotional energy expended and created by learning efforts. Though short-lived, this interest

focuses attention, enhances cognitive performance and learning, and improves integration (Hidi &

Renninger, 2006). For Ainley (2012), interest functions as a "hook": A learning activity that

sparks interest easily engages students, and the learning process begins. For most scales that we

investigated, enjoyment and interest were central components to positive EE.

These factors matter in blended and online learning. Tempelaar, Niculescu, Rienties,

Gijselaers, and Giesbers (2012) found significant correlations between students' engagement in

the online component of BL and their self-reported levels of enjoyment. They reported no clear

correlation between face-to-face engagement and achievement emotions including enjoyment,

boredom, anxiety, and hopelessness. However, the proxy measure they employed to estimate

face-to-face engagement was the number of clicks in the LMS, a questionable substitute for the fidelity, synchronicity, and humanness available in face-to-face settings (Graham, 2006).

Happiness research is complex (Oishi, Diener, & Lucas, 2007), with various definitions of the constructs. Some define happiness as a relatively stable feeling towards life, noting its association with better social and marital relationships, longevity, higher income, and lower unemployment (Oishi et al., 2007). As an indicator of engagement, however, we are interested in happiness as a more momentary state expressing engagement in a learning task. This state of happiness is similar to the mild joy and contentment that Fredrickson (2001) found to be associated with increased creativity and cognitive performance.

In TML research this state of happiness has been examined (D'Mello, Lehman, & Persons, 2010; Lehman, D'Mello, & Persons, 2008) and found among the more frequent affective states experienced by learners when interacting with technology (D'Mello, 2013). As an indicator of engagement, we expect happiness to occur after engagement-facilitating experiences, such as receiving positive feedback, attaining learning goals, and resolving confusion or other impasses (D'Mello, 2013; Lehman et al., 2008; Stein & Levine, 1991). D'Mello et al. (2010) found that when students using an ITS reacted with happiness to feedback on one problem, their performance improved on subsequent problems: as our overall logic model suggests, learners' POS improved their learning outcomes. Some have argued that engagement (along with pleasure and meaning) can be a key pathway to happiness; thus happiness may result from and indicate an engaged state (Parks, Schueller, & Tasimi, 2013; Seligman, Ernst, Gillham, Reivich, & Linkins, 2009). Future research could investigate these pathways with increasingly fine-grained and real-time tools available to recognize expressions of happiness, including facial action coding, posture, and eye-tracking (D'Mello & Graesser, 2012; D'Mello et al., 2010).

We propose *confidence* as a third dimension of POS. Confidence provides a clear

contrast to the NEG factor (suggested by Skinner and colleagues) of anxiety (Kort, Riley, &

Picard, 2001); research indicates an inverse relationship between the two (Pajares, 1996; Shea &

Bidjerano, 2010). It is possible that confidence may double as both an indicator and a facilitator

of engagement. Confidence may precede and facilitate engagement: students are more likely to

exert effort in academic tasks if they believe they have the capacity to succeed (Greene, 2015;

Hulleman, Godes, Hendricks, & Harackiewicz, 2010; Milligan, Littlejohn, & Margaryan, 2013;

Shea & Bidjerano, 2010). But confidence may also indicate engagement: self-reports of

confidence "depen[d] on events that occurred in [solving] the previous problem and not on

[learners'] incoming beliefs" (Arroyo et al., 2009, n.p.). In subsequent testing of this model, we

will frame items to measure not only learners' general confidence in a course, but their

confidence during or immediately after particular learning activities. Arroyo et al. (2009) used

physiological sensors and frequent self-report to create models of confidence (plus frustration,

excitement, and interest) for students interacting with an ITS to learn math. One kind of

confidence—belief in one's ability to work with computers (called *computer self-efficacy* or

technical confidence [Conrad & Kanuka, 1999])— may be of particular relevance in blended and

online learning in which confidence in one's technical abilities might facilitate engagement in or

reflect perceived success during computer-mediated activities.

Negative EE (NEG). Skinner and colleagues found emotional disengagement to be a

multidimensional construct consisting of *enervated emotion* (tiredness, sadness, boredom),

alienated emotion (frustration, anger), and *pressured participation* (anxiety; see Skinner,

Kindermann, & Furrer, 2009); D'Mello (2013) noted that frustration and boredom are critical in

learning with technology. We propose that NEG is comprised of three first order factors:

boredom, frustration, and anxiety. This is a narrower configuration than Skinner and colleagues

employ. The emotions they group as enervated emotion—sadness, tiredness, and boredom—are

considered discrete emotions by other researchers (Russell, 2003; Segura & Gonzalez-Roma,

2003). In research to evaluate cognitive-affective states during TML, the unit of analysis is

usually the discrete emotion (boredom, not enervated emotion). We will employ the narrower

unit so that our framework may be applicable to such methodologies.

Baker et al. (2010) defined *boredom* as weariness or restlessness due to lack of interest.

Skinner, Kindermann, Connell, and Wellborn (2009) called boredom "a sufficient condition for

lack of effortful involvement" (p. 226). Such weariness and lack of involvement indicate the

absence of emotional energy towards learning. Boredom may threaten CE "by reducing cognitive

resources, undermining both intrinsic and extrinsic motivation, and promoting superficial

information processing" (Pekrun, 2011, p. 31).

In studying TML, Baker et al. (2010) found that boredom occurred during approximately

5% of the times examined as students interacted with different computer-based learning

environments. Though infrequent, once boredom settled in, it was an especially persistent

affective state that could "reduce learning more than other cognitive–affective states by leading

students to engage in gaming behaviors which are associated with poorer learning" (p.

236). Researching ITSs, Lehman, D'Mello, and Person (2008) labeled boredom "the least

productive state" (n.p.); frustration and confusion at least indicated investment in the learning

process. In his meta-analysis of the affective states experienced in TML environments, D'Mello

(2013) found that boredom and frustration were more likely in laboratory studies with simple

computer interfaces. In contrast, engagement was more frequent in studies conducted in authentic

learning contexts using advanced learning technologies (such as ITSs, animations and

simulations, and immersive educational games) with enhanced interactivity and human-like

communication capabilities. Thus, preserving interaction and humanness may increase

engagement and decrease boredom and frustration.

Skinner, Kindermann, and Furrer (2009) grouped frustration and anger under the heading

of *alienated emotion*, whereas Pekrun and Linnenbrink-Garcia (2012) combined these two as

negative activating emotions. We will focus on *frustration*, the more common of the two during

learning with technology (D'Mello, 2013) and situate it as another first order factor in

NEG. When Dennerlein, Becker, Johnson, Reynolds, and Picard (2003) frustrated computer

users (through poor software usability), they found increased physical risk associated with

musculoskeletal and cardiovascular disorders. Baker et al. (2010) noted that frustration "may

lead students to use (or fail to use) learning environments in ways that reduce their

learning." Even so, they acknowledged that frustration (and confusion—see below) "may be a

natural and unavoidable part of the experience of learning when difficult material is encountered .

. . a byproduct of positive learning experiences" (p. 235). They found that frustration and

confusion rarely led to gaming the system at levels caused by boredom, even titling an article

"Better to Be Frustrated than Bored."

Anxiety is the last first order factor in our proposed NEG construct. Pekrun (2011)

explained that any emotion could deplete cognitive resources, but "resource consumption effect is

likely bound to emotions that have task-extraneous objects and produce task-irrelevant thinking,

such as worries about impending failure" (p. 27). Pekrun noted that on simple tasks anxiety may

not affect or may even enhance performance, but on complex or difficult tasks that demand

cognitive resources, learning is impaired (see p. 30). Thus anxiety may be most deleterious to

emotional and cognitive energy reserves in complex learning contexts.

Regardless of the complexity of the learning task, some students may find nontraditional settings like blended or online instruction to produce anxiety. Conrad (2010) described adult learners beginning a completely online course: "Their anxiety level is universally high, even among those who have already completed many online courses" (p. 220). Without a face-to-face component, Conrad continued, "It is hard to demonstrate empathy without a facial nod or smile. Words alone, which are all online educators have at their fingertips, often fail to convey a deep sense of humanness" (p. 214). Hermes et al. (2009) found that female rats kept in isolation developed 84 times as many mammary tumors as female rats in groups, along with increased levels of stress hormones and anxious, fearful behavior (see also Pinker, 2014). If we too have less anxiety when we are with other humans, the face-to-face component in BL becomes key to reducing negative EE.

Researchers have debated whether *confusion* is a cognitive state, an emotion, or even an affective state that is not an emotion (D'Mello, Lehman, Pekrun, & Graesser, 2014). Confusion arises with cognitive disequilibrium, when incoming information does not seem to align with existing knowledge structures (Graesser, Lu, Olde, Cooper-Pye, & Whitten, 2005). This can be productive to learning, as D'Mello et al. (2014) noted: when "there is a discrepancy in the information stream and the discrepancy is identified and corrected. . . , one important form of deep learning occurs" (p. 155). D'Mello's meta-analysis (2013) found confusion the second most frequent emotion (of 17) among students interacting with learning technologies; thus we must recognize its role in learner engagement. Thus far, researchers have found varied effect depending on contextual details. When accompanied by enjoyment, curiosity, or confidence, confusion spurs engagement and learning; when combined with boredom or frustration, it correlates with disengagement and lower learning outcomes (Baker et al., 2010; D'Mello et al.,

2014). Future research can investigate the interplay of confusion with other first order factors such as frustration, boredom, and interest and whether confusion aligns more with POS or NEG.

EE is indispensable to the learning process, a "fuel" (Skinner & Pitzer, 2012, p. 33) for high quality learning and the "antecedent of other components of engagement" (Pekrun & Linnenbrick-Garcia, 2012, p. 260). The importance of emotion to cognition and learning is conveyed by findings that human tutors spend at least as much time dealing with affective and motivational goals as they do with cognitive and informational challenges (Lepper, Woolverton, Mumme & Gurtner, 1993). The ability to deal with the emotions that arise during learning may help explain why human tutors are "unrivaled in their ability to promote deep and lasting learning" (Paul, 2014). Human actors are more adept at managing EE than are computers, but that does not mean that computer-mediated resources are not sufficient or even more expeditious to learning in certain situations. In BL environments, where the decisions to blend human- and computer-mediated instruction must consider the effect upon learner engagement, instructional designers need to understand when human-human interaction is necessary to maintain EE and when computer-mediated resources are desirable.

Research can investigate how the affordances of BL impact EE. BL's additional channels for interactivity—with asynchronous online discussions increasing flexibility and opportunity for reflection, and in-class interactions promoting spontaneity and human connection (Graham, 2006)—might result in "absolutely richer interaction" (Gedik, Kiraz, & Ozden, 2012, p. 108). Improved personalization could increase interest and confidence while curtailing boredom, frustration, or anxiety. Immediate feedback from online tools could lessen confusion, frustration, and anxiety. On the other hand, BL may introduce barriers, such as increased workload or technical difficulties (Gedik et al., 2012), which increase frustration, anxiety, and confusion.

Conclusion

We began by mentioning three challenges to researching learner engagement in blended settings. The dynamic nature of BL and the diverse ways of combining human- and technology-mediated instruction make the ability to measure engagement under different conditions all the more important. To do this, we need greater clarity about the definitions and constructs of engagement. We have proposed a theoretical framework for learner engagement, grounded in existing engagement literature and contextualized for blended settings, which can add conceptual clarity and direction for future research. We have tried to maintain the distinction between indicators and facilitators, for "research and intervention efforts require a clear demarcation between these two" (Skinner et al., 2008, p. 766).

At times, however, the distinction is blurred. As noted, confidence may function as both facilitator and indicator. We also considered including *perceived relevance* and *perceived challenge* as cognitive indicators of engagement. A learner who perceives the relevance of a learning activity may be further cognitively engaged (Assor, Kaplan, & Roth, 2002; Frazee, 2003; Wang & Eccles, 2013), and relevance interventions can trigger interest in learning exercises (Hulleman et al., 2010). In these examples perceived relevance precedes and facilitates. But the reverse is also true: CE manifests itself in increased perception of relevance. O'Neill et al. (2015) considered academic engagement to be indicated by four factors including intrinsic valuing and motivation, measured using items that assessed relevance. However, early results from experience sampling research being done by our team show relevance functioning as a facilitator rather than an indicator of engagement.

Csikszentmihalyi's theory of flow argues that a balance between *perceived challenge* and learner skill is a critical factor to learner engagement (Csikszentmihalyi, 1990; Shernoff et al.,

2003). Fredricks et al. (2005) found task challenge to be a significant predictor of cognitive

engagement, and the self-system process model contends that learners are more likely to be

engaged when they perceive optimal challenge on meaningful or enjoyable tasks (Connell &

Wellborn, 1991). Mahatmya, Lohman, Matjasko, and Farb (2012), using a bioecological theory

of human development and the person-environment fit perspective, listed three elements to their

conceptualization of CE: attention to task, mastery of task, and preference for challenging

tasks. In each of these propositions, the perception of an optimal level of challenge abets and

facilitates engagement. Though perceived relevance and perceived challenge are not included as

engagement indicators in our model, we believe they may be important facilitators of

engagement. We have some knowledge (and need more) about factors with potential to facilitate

BL engagement.

To assess the impact of these and other facilitators, we must know what indicates

engagement. We have proposed the same indicators for engagement in face-to-face and online

contexts, but this assumption must still be tested: does engagement manifest itself differently in

face-to-face settings than in online settings? Factor analysis research could determine whether,

for example, face-to-face curiosity and online curiosity are comparable in factor loadings and

estimated intercepts, or whether they are unique constructs.

At the same time, when examining BL engagement, we must also think beyond the

physical attributes of face-to-face and online instruction. As Graham (2013) noted, "[P]sycho-

social relationships are the issues at the core of BL research and design" (p. 346). We need to

better understand how engagement indicators are affected by human and by machine

interaction. In the first fMRI study to compare brain responses to live interactions versus

prerecorded ones, Redcay et al. (2010) found that live interaction sparked greater activity in brain

regions associated with attention. What might be seen if researchers could likewise examine brain activity in regions associated with curiosity, enjoyment, or anxiety? Is face-to-face human interaction the gold standard (as often accepted) in encouraging learner engagement? Or are some engagement indicators equally propelled by computer-mediated human interaction or even by machine interaction, with its affordance of near-instant feedback in certain situations?

To answer such questions, research is needed not only at the completion of a blended course, but throughout the course at the activity level. In future research we will use an end-of-course survey to attempt to operationalize and test this framework, but will also compare the results to log data and to experience-sampling surveys collected biweekly in blended courses. Possibly engagement indicators function differently at the activity and course levels: confusion noted in real time might be an indicator of focused engagement (D'Mello, et al., 2014), but confusion recalled much later (e.g., in an end-of-course survey) might indicate residual frustration and anxiety. By examining activity- and course-level engagement, we can study relationships between intervention strategies (both human- and machine-driven), learning pathways, and engagement (D'Mello & Graesser, 2012).

Blended contexts expand the methods for collecting data to measure engagement (Henrie, et al., 2015), and this paper has referenced many ways of collecting data on various engagement indicators. Due to both the complex nature of engagement and the differences inherent to measuring it in multiple contexts, research on engagement in BL settings will often require mixed methods for collecting data. Research on BL engagement ought to be increasingly real-time, minimally intrusive, and maximally generalizable across various subject matter contexts. Yet these aims sometimes conflict with one another or with the need for scalability. Experience-sampling methods ask learners to report on both internal (thoughts, feelings, mood) and external

(date, time, location, companions, activities) dimensions of specific experiences (Fleeson, 2007; Hektner, Schmidt, & Csikszentmihalyi, 2007); this method results in considerable amounts of quantitative and qualitative data but is fairly obtrusive. Collecting machine-generated log data is unobtrusive, but interpretability regarding CE and EE is questionable. We look forward to advances in BL engagement research that address these challenges.

This framework advances inquiry about BL engagement by establishing a set of indicators rooted in theory and literature. At a time when learner engagement is considered "the holy grail of learning" (Sinatra, Heddy, & Lombardi, 2015, p. 1) and interventions are touted for their ability to improve engagement, we need a clear model from which to design and evaluate. Though our model is only an outline of the principal factors indicating learner engagement, it is a starting point with the potential to further our understanding of engagement in BL settings.

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Article 2: Scale Development to Measure Learner Engagement

in Blended Learning Environments

Scale Development to Measure Learner Engagement

in Blended Learning Environments

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Abstract

Learner engagement correlates to student satisfaction, achievement, and persistence, outcomes important to educators, students, and researchers. In the quest to improve learner engagement, many have thought that the integration of face-to-face and online instruction—frequently called blended or hybrid learning—might provide "the best of both worlds." However, determining whether particular blended interventions actually lead to increased learner engagement requires clear models and measures of engagement. Halverson and Graham (under review) recently proposed the first theoretical framework to guide inquiry and practice into blended learning engagement. This research was undertaken to operationalize and test their proposed model of blended learning engagement using exploratory and confirmatory factor analysis. To do so a new instrument to measure blended learning engagement was developed and the structural validity investigated from a sample of 571 students from two universities in the Intermountain Western United States. Results showed the related but nevertheless distinct nature of face-to-face and online engagement. We also found that indicators considered behavioral in some alternative models of engagement were empirically indistinguishable from cognitive indicators. The instrument, the Blended Learning Course Engagement Survey, takes into account context (online or face-to-face) and the cognitive and emotional aspects of learner engagement in such settings. We discuss contributions this framework and scale can make to theory and pedagogy.

Keywords: learner engagement; cognitive engagement; emotional engagement; blended learning; scale development; factor analysis

Introduction

Blended learning, defined as the integration of face-to-face and online instruction (Aspden & Helm, 2004; Graham, 2006), is increasingly the norm in educational settings today (Murphy, Snow, Mislevy, Gallagher, Krumm, & Wei, 2014; Picciano, Seaman, Shea, & Swan, 2012; Staker, Chan, Clayton, Hernandez, Horn, & Mackey, 2011). However, since effective blending can involve innumerable instantiations of human- and technology-mediated instruction, practitioners and researchers alike are uncertain as to which blended designs most efficaciously increase learner engagement.

Supporting learner engagement is no insignificant goal. Learner engagement—the investment of cognitive and emotional energy to bring about a learning task (Halverson & Graham, under review; Schunk & Mullen, 2012)—has been correlated with academic achievement (Hughes, Luo, Kwok, & Loyd, 2008; Ladd & Dinella, 2009), student satisfaction (Filak & Sheldon, 2008; Zimmerman & Kitsantas, 1997), and persistence (Berger & Milem, 1999; Kuh, Cruce, Shoup, Kinzie, Gonyea, & Gonyea, 2008). With such influence, it is not surprising that learner engagement has been termed "the holy grail of learning" (Sinatra, Heddy, & Lombardi, 2015, p. 1), "an educational bottom line" (Coates, 2006, p. 36). But no definition of learner engagement is universally accepted at present, especially in the blended context, and Henrie, Halverson, and Graham (2015) found confusion among the terms and operationalizations of engagement in research that measured learner engagement in technology-mediated settings.

To advance research on the impact of blended designs on learner engagement, we require greater theoretical and definitional clarity about blended learning engagement. To this end Halverson and Graham (under review) examined existing literature on learner engagement, identified constructs most relevant to blended learning, and proposed the first theoretical

framework for learner engagement in blended settings. They had been dissatisfied with existing

models of learner engagement in relation to blended learning. Models like the National Survey of

Student Engagement (NSSE; Kuh, 2009) and the Student Engagement Questionnaire (Coates,

2006), focused on institutional level engagement (Skinner & Pitzer, 2012), "a different reality

than engagement in the classroom or, even more circumscribed, in learning activities" (Janosz,

2012, p. 698). Other models ignored cognitive engagement (CE; see Skinner, Furrer, Marchand,

& Kindermann, 2008 and Skinner, Kindermann, & Furrer, 2009). Across the existing models

they found confusion in definitions and constructs (see also Henrie, Halverson, & Graham, 2015).

No theoretical framework existed that was appropriate for blended learning engagement.

Thus Halverson and Graham (under review) proposed a new model, arguing that the most

fundamental indicators of engagement are those that demonstrate learner investment of mental

and emotional energy in the learning process (see also Astin, 1984; Janosz, 2012; Schunk &

Mullen, 2012). Some models of learner engagement include behavioral engagement, but

Halverson and Graham argued that behavioral factors are actually outward displays of the

underlying cognitive and emotional energies that fuel learning. Their model suggested that

cognitive engagement (CE) is composed of *attention, effort and persistence, time on task,*

cognitive strategy use, absorption, and *curiosity* (see Figure 1). The first three factors were

theorized to indicate *quantity* of CE, while the last three were thought to indicate *quality*.
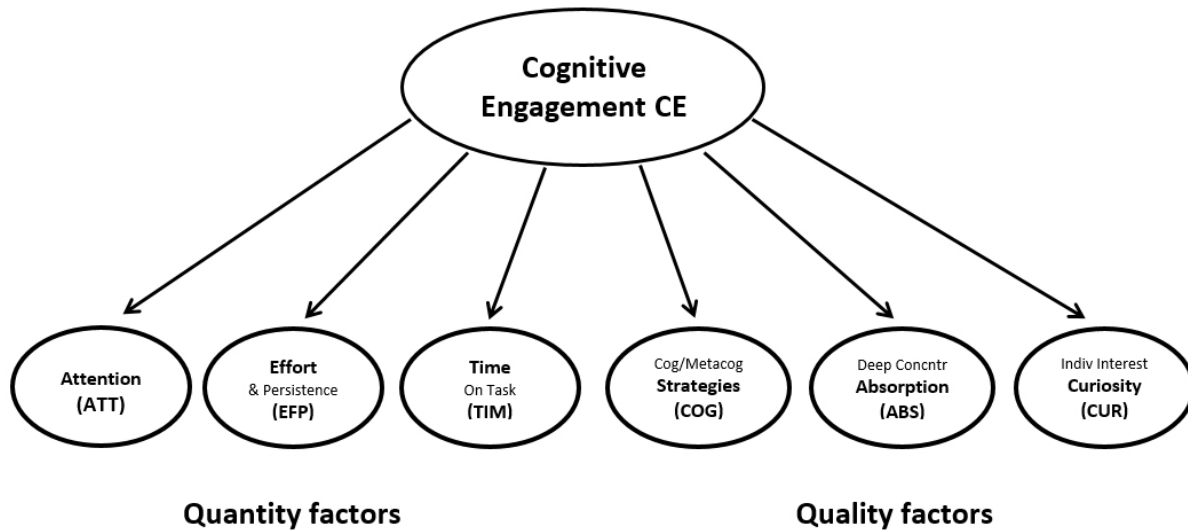
Figure 1. Theoretical Model of Cognitive Engagement. Attention, effort and persistence, and time on task were theorized to indicate the quantity of cognitive engagement, while cognitive strategy use, absorption, and curiosity were thought to indicate its quality.

Emotional engagement (EE), Halverson and Graham proposed, consists of positive energy indicators, including *interest and enjoyment, happiness*, and *confidence*, along with negative energy indicators such as *boredom, frustration*, and *anxiety* (see Figure 2). They noted research suggesting that *confusion* may indicate positive or negative energy, depending on the concurrent emotions. When interest is present, confusion may accompany increased EE, but when boredom or frustration is present, confusion decreases EE and may lead to gaming the system or otherwise disengaging (Baker, D'Mello, Rodrigo, & Graesser, 2010; D'Mello, Lehman, Pekrun, & Graesser, 2014). Halverson and Graham advocated further research to determine the place of confusion in the theoretical model.

Emotional Engagement EE
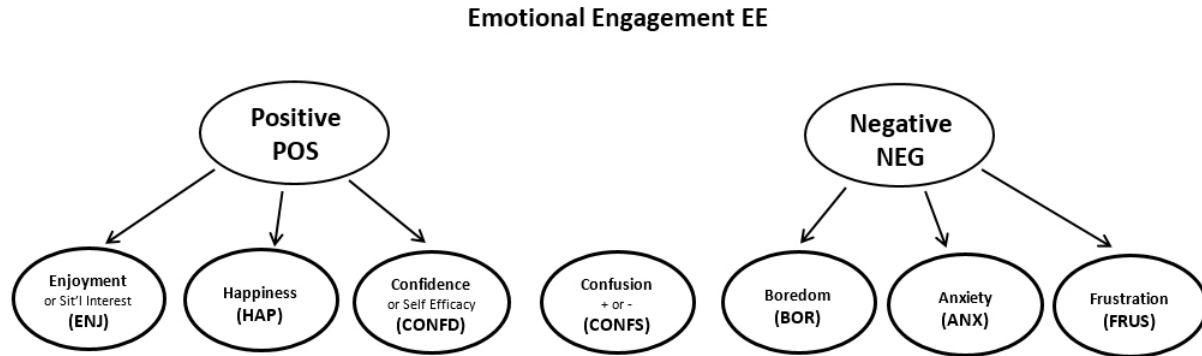
Figure 2. Theoretical Models of Emotional Engagement (Positive and Negative). The factor of Confusion was left unattached, for confusion affects engagement and learning differently depending on contextual details.

Halverson and Graham's engagement framework (under review) was grounded in engagement literature, applied to the affordances of blended learning, and presented as a theoretical construct paper. Our goal was to empirically test this model by developing and testing the structural validity of an instrument based on its framework of learner engagement.

Method

The present study operationalized Halverson and Graham's proposed model of blended learning engagement (currently under review) through an end-of-course survey. While survey methodology is not the only, or perhaps even the best, way to measure learner engagement, it is the most common (Henrie, Halverson, & Graham, 2015). The survey probed each theoretical subconstruct using question pairs that applied each to face-to-face and online modalities.

Item Generation

Halverson and Graham (under review) drew upon a vast array of existent literature to form their theoretical model of learner engagement in blended settings. Their review of the engagement literature and consideration of the affordances of blended contexts provided strong content validity on which to base our scale. To operationalize the theorized constructs and

generate items for our scale, we consulted various related instruments. Table 1 gives a partial list

of sources we consulted in generating items. We found that very few of the items matched our

purposes without alteration. For example, we appreciated Skinner and colleagues' model of

engagement, but felt its lack of a cognitive factor neglected one of the most significant aspects of

engagement. We corresponded with their research team and learned that, although they felt CE

was "worthy of investigating," they did not "yet have measures to capture the cognitive

component, and aren't actively working on developing them at this time" (J. Pitzer, personal

communication, January 6, 2014). They did, however, share with us the alterations they had

made to their existing scales, which are usually implemented in K-12 settings, in order to fit a

higher education context.

Table 1

Sources Consulted in the Development of Items

Construct & Subconstruct	Sources Consulted in Item Development
Cognitive Engagement	
Attention	Chi and Skinner (personal communication, January 20, 2014)
	Dornbusch and Steinberg (1990)
	Skinner, Kindermann, and Furrer (2009)
Effort and Persistence	Oliver (2007)
	Finn, Boyd-zaharias, Fish, and Gerber (2007)
	Pintrich, Smith, Garcia, and McKeachie (1991)
Time on Task	Dornbusch and Steinberg (1990)
	Pintrich, Smith, Garcia, and McKeachie (1991)
Cognitive and Metacognitive	Mokhtari and Reichard (2002)
Strategy Use	Pintrich, Smith, Garcia, and McKeachie (1991)
	Wolters (2004)
Absorption	No direct sources, but based on Csikszentmihalyi (1990)
Curiosity	Agawal and Karahanna (2000)
Positive Emotional Engagement	
Enjoyment/Situational Interest	Chi and Skinner (personal communication, January 20, 2014)
	Singh, Granville, and Dika (2002)
	Skinner, Kindermann, and Furrer (2009)
Happiness	Skinner, Kindermann, and Furrer (2009)
Confidence	Pintrich, Smith, Garcia, and McKeachie (1991)
Negative Emotional Engagement	
Boredom	Chi and Skinner (personal communication, January 20, 2014)
	Skinner, Kindermann, and Furrer (2009)
Frustration	Chi and Skinner (personal communication, January 20, 2014)
	Skinner, Kindermann, and Furrer (2009)
Anxiety	Chi and Skinner (personal communication, January 20, 2014)
	Martin (2009)
	Pintrich, Smith, Garcia, and McKeachie (1991)
	Skinner, Kindermann, and Furrer (2009)
Confusion	No direct sources. D'Mello (2013) finds that confusion is one of the most frequent emotions when learning with technology.

The most significant needs we found to alter or invent items developed because existing

surveys of learner engagement fail to address both the face-to-face and online settings included

in blended learning. Most investigate only face-to-face settings, although some instruments that

measure engagement in face-to-face contexts have been adapted for online use (Rowe, Shores,

Mott, Lester, & Carolina, 2011; Sun & Rueda, 2012). The widely used NSSE has been applied

to online settings (Henrie, Halverson, & Graham, 2015), but as stated earlier its focus is

primarily institutional-level engagement, and thus it does not help us understand course- and

activity-level interventions. Most existing engagement instruments contain numerous items that

transfer poorly to blended contexts; thus revalidation of any adapted items has been required.

Halverson and Graham (under review) proposed that the same constructs indicate engagement in

face-to-face and online contexts, but acknowledged that this assumption must be tested and that

engagement might manifest itself differently in the two settings. We created paired questions

with similar wording to inquire about engagement during face-to-face and online learning

experiences. For example, to measure absorption, a CE indicator, we included the following

pair: "I became absorbed in face-to-face learning activities for this course" and "I became

absorbed in online learning activities for this course." We developed multiple items probing

each CE and EE factor.

To collect formative feedback, 57 students in a blended world civilization course taught

by the first author were invited on the last day of class to complete a pilot version of the

instrument. Though not enough data were collected for a full exploratory factor analysis (EFA)

or confirmatory factor analysis (CFA), the results were informative for improving the individual

items, the model, and the overall instrument before our full-scale data collection. We decided to

avoid using bipolar and unipolar items in the same survey, especially regarding the same

constructs. First, consistency in response categories is advisable for respondent clarity and later ease of analysis. Additionally, only some of the bipolar items in the original instrument featured opposite constructs that were both of interest to our model (e.g., boredom and interest). Other bipolar items included an opposite construct not relevant to our work. For example, items asked students to rate their level of confusion/clarity during a variety of learning activities, but Halverson and Graham's theoretical framework only features confusion, not clarity. This formative process helped us refine our end-of-course survey items.

We next conducted cognitive interviews (Campanelli, 2008; Dillman, Smith, & Christian, 2009) to ensure that the items would be understood by potential respondents. We administered the revised instrument to undergraduates at one of the universities where the instrument would be utilized. Those students were asked to think aloud as they considered each item, and two graduate students took notes on their reflections. Based on student comments, we revised the wording of a number of items to improve the clarity and intended interpretation of each.

In the revised instrument (see Appendix), most of the first order engagement factors were represented by three question pairs each, though time on task featured only two item pairs, and a few constructs featured four pairs. Eight items inquiring about perceived challenge and perceived relevance were present in the survey but excluded from the framework and the analysis that follows. Pairs were similarly worded questions that inquired into face-to-face and online contexts: for example, "Describe your level of attentiveness in face-to-face class" and "Describe your level of attentiveness during online work for this course." Response format collected categorical data using a five point Likert-type scale ranging from 1 (*never*) to 5 (*all the time*) or other five-response variations such as 1 (*not at all interested*) to 5 (*extremely interested*). To decrease the likelihood of response acquiescence (Jayanti, McManamon, & Whipple, 2004),

some items were negatively stated; these items were subsequently reverse-scored before we proceeded with data analysis.

Data Collection

The target population consisted of undergraduate students in blended courses at two four-year universities in the Intermountain West. Blended learning designs varied, and subject matter covered topics from finance and chemistry to nursing and the humanities, as we hoped to develop an instrument measuring learner engagement across various disciplines and blends. Most courses were three-unit general education and introductory courses, neither upper-level nor specialized.

At the end of fall 2014, we emailed an invitation to potential participants from 11 blended courses to participate in the end-of-course learner engagement survey, requiring approximately 10-15 minutes. Some students were part of a larger research study that also collected log data, experience sampling responses, and learner characteristics; others were solicited only for the end-of-course engagement survey. We utilized an implied consent format for their participation and we collected no identifying information. Students were emailed a link to the online survey in Qualtrics, an online survey software platform. Some professors requested that students not receive the survey until final exams had concluded; thus vacations may have reduced response rate in such classes. Response rate varied by class from 14% to 63%; thus results may not be fully generalizable as we have no simple way of determining whether there was a pattern of missingness. A total of 571 students began the survey, though some failed to complete all questions.

Analysis

This research used factor analysis "to examine empirically the interrelationships among the items and to identify clusters of items that share sufficient variation to justify their existence

as a factor or construct to be measured by the instrument" (Gable, 1986, p. 85). Halverson and

Graham's (under review) proposed theoretical framework and the corresponding instruments are

new and untested, though grounded in the learner engagement literature. Using M*plus* version

7.31, we ran an initial CFA to test the theoretical framework. Since model fit was not ideal, we:

(a) randomly sampled half of the data, with the remaining data used for validation, (b) ran an

EFA and a series of CFAs on the training dataset, and (c) ran the final model on the validation

set. EFA allowed us "to identify the underlying dimensions of a domain of functioning, as

assessed by a particular measuring instrument" (Floyd & Widaman, 1995, p .286), and additional

CFAs allowed us to "examin[e] the derived constructs in light of the theoretical predictions that

follow from the literature review and the operational definitions of the targeted categories . . ."

(Gable, 1986, p. 87). Our goal was to find models for CE and EE that displayed good model fit

and were comprised of constructs with both convergent and discriminant validity.

Results

Descriptive Statistics

Excluding a few items dropped for reasons explained below, the mean scores of all items

ranged from 2.13 to 4.09, and the standard deviations ranged from .777 to 1.349. The skew

indices ranged from -.849 to .856, and the kurtosis indices from -1.258 to .835. The data in this

study were considered to be univariate normal based on Kline's (2011) recommendations that

values around .70 are "adequate," those around .80 are "very good," and those around .90 are

"excellent" (p. 70).

Cognitive Engagement

Halverson and Graham (under review) proposed that CE is composed of *attention, effort*

and persistence, time on task, cognitive strategy use, absorption, and *curiosity*. In order to reach

our goal of good model fit with constructs displaying convergent and discriminant validity, we

tested five models, described in further detail below. Our first model, CE Model 1, was based on

Halverson and Graham's theoretical constructs and did not separate indicators by context, but

this had poor model fit. A subsequent EFA showed context as the clearest element in factor

structure, so we decided to test face-to-face indicators only, select the best-fitting models, and

then use invariance testing across context to determine whether the online indicators were

comparable. We tested a five-factor model based on the theoretical first order factors (CE Model

2). Although model fit was good, several factors lacked discriminant validity. We respecified

the models to take factor intercorrelations into account, and then tested two two-factor models

featuring the constructs of focused attention and curiosity (CE Model 3), and effort and flow (CE

Model 4). These showed very similar model fit. Considering the several high factor

intercorrelations, a single factor model (CE Model 5) was tested, but did not display acceptable

model fit and was rejected.

Initial confirmatory factor analysis. Since our scale was based upon a substantive

theoretical framework, we chose to run an initial CFA (CE Model 1 in Table 2) using our entire

sample set ($n = 558$) to test the strength of the CE framework. Halverson and Graham (under

review) did not make a definitive claim about the effect of context, but wrote: "We have

proposed the same indicators for engagement in face-to-face and online contexts, but this

assumption must still be tested: does engagement manifest itself differently in face-to-face

settings than in online settings?" Thus in these initial CFAs we ran the models without the

context condition, that is allowing all items purported to measure attention, for example, to be

grouped under the first order construct attention, without dividing them into *online attention* and

face-to-face attention. Then all the first order constructs were specified to measure a second

order factor, CE. The model was estimated using weighted least squares (WLSMV)—useful for categorical data as well as smaller sample sizes (Brown, 2006). However, we also compared factor loadings estimated using WLSMV and MLR; results were similar, suggesting that there was no method effect and that our data was 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). While the second order factor CE had significant loadings from all first order factors (all standardized loadings above .900 except curiosity [CUR] at .736), within the first order factors the face-to-face and online items differed in their measurement sensitivity, with online items loading much lower than their face-to-face equivalents. For example, the item ATT_F3 loaded onto attention (ATT) at .844, while its online counterpart, ATT_O3, loaded at .476. Online items also had weaker R^2 estimates than did their face-to-face counterparts. Model fit is often considered good when within these parameters: RMSEA < .08 (Browne & Cudeck, 1993; Byrne, 2013; MacCallum, Browne, & Sugawara, 1996), CFI > .95 (Hu & Bentler, 1998, 1999), and TLI > .90 (Wang & Wang, 2012). According to these standards, our model fit was poor for CE when context was not taken into account (RMSEA = .125, CFI = .630, TLI = .591). The Chi-square test of model fit was χ^2 = 5675.487 (df = 588). These results suggested that this model had been misspecified and needed to be modifyied.

We also concluded that the first order factor of time on task should be dropped. First, all the indicators had particularly low factor loadings, suggesting that the construct could not be measured well using the data. The time construct only contained two question pairs. One pair asked, "How often did you spend the expected amount of time in face-to-face class/completing online work for this course?" These questions may have had different meanings to students based on the course blend, as some sections required face-to-face time and others made

classroom fathering an optional workshop experience. The face-to-face item, though still within bounds of univariate normalcy, had the highest mean (4.44) and kurtosis index (3.090) as well as the lowest skew index (-1.919). For these reasons, while time on task may still indicate CE, we removed the time items from subsequent analyses discussed here.

Exploratory factor analysis. To analyze the 32 remaining CE items, we first randomly divided the total sample into two split-half samples using the Statistical Package for the Social Sciences (SPSS, version 22). We tested the factorability of the data using Bartlett's test of sphericity (Bartlett, 1954), and then examined the sampling adequacy using the Kaiser-Meyer-Olkin (KMO) test (Kaiser, 1958). Findings indicated a significant test for Bartlett's test of sphericity (χ^2 (496) = 3942.786, p < 0.001) and a KMO value of 0.862, indicating that the data were suitable for structure detection (Tabachnick & Fidell, 1989). Subsequently we used M*plus* version 7.31 to carry out an exploratory factor analysis with an oblique geomin rotation and, with the indicators declared categorical, a WLSMV estimation of the first split-half sample ($n = 290$). This result suggested seven factors with eigenvalues over 1.0 (Kaiser's eigenvalue-greater-than-one rule). A scree plot inspection, on the other hand, suggested three or four factors. We also considered the interpretability of different factor solutions. Specifically, the two-factor structure suggested a *face-to-face CE* factor reflected by all 16 items inquiring into the face-to-face context and an *online CE* factor reflected by all 16 items inquiring into the online context. These two factors were correlated ($r = .177, p < .01$). All face-to-face items but one (ABS_F2) had standardized loadings greater than .500 ($p < .001$), but again the online items had a unique pattern, with standardized loadings generally lower than their face-to-face pairs, ranging from .271 (RATT_O2) to 847 (ABS_O3), all significant ($p < .001$). The three- and four-factor structures again suggested the *face-to-face* and *online CE* factors as the first and second factors,

but the third and fourth factors crossed context boundaries, clustering *face-to-face* and *online*

curiosity, for example. Additionally, the third and fourth factors were less interpretable overall

and included items that double-loaded on the first two factors.

Clearly, these exploratory factor analyses pointed to a strong context effect. Online and

face-to face engagement appeared to be unique though correlated constructs. In our next step,

using CFA we first tested a few variations of our model using face-to-face items only.

Confirmatory factor analysis of face-to-face CE items. We ran several CFAs on the

same half of the sample employed for the EFAs. To establish the validity of the scale, we

conducted a first order CFA (CE Model 2 in Table 2) on the data. Since we had decided to

eliminate the time-on-task factor from our analysis, we hypothesized a correlated five-factor CE

measurement model (Figure 3). Results suggested a good fit: RMSEA = .069, CFI = .977, and

TLI = .971. All indicators measured their respective factors fairly well, with all standardized

parameters estimates ranging from .623 to .932 ($p < .001$) except for one (ABS_F2, .435).

However, the factor intercorrelations (.688-.994) suggested that some of our first order factors

lacked discriminant validity (Kline, 2011). The one first order factor with most noticeable

discriminant validity was curiosity, which had factor intercorrelations of .688 to .755, except

with absorption ($r = .851$).
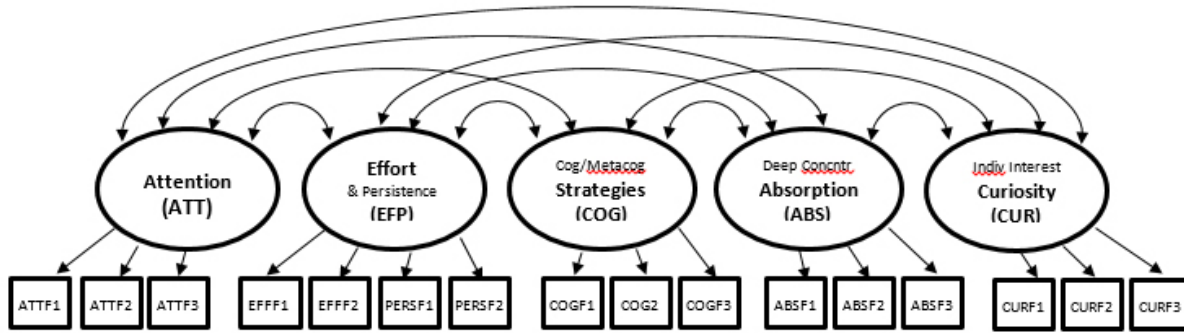
Figure 3. Face-to-Face CE Model 2, with five first order factors: attention, effort and persistence, cognitive strategy use, absorption, and curiosity.

Thus we next hypothesized a correlated two-factor CE measurement model (CE Model 3 in Table 2) with *focused attention* (FOC_F, specified by attention, effort and persistence, cognitive strategy use, and absorption indicators) and *curiosity* (CUR_F) (Figure 4). Results suggested an acceptable fit: RMSEA = .085, CFI = .962, and TLI = .956. Indicators measured their respective factors fairly well (.412 to .855 for FOC_F, .750 to .874 for CUR_F, $p < .001$). The intercorrelation between focused attention and curiosity was acceptable (.793, $p < .001$).
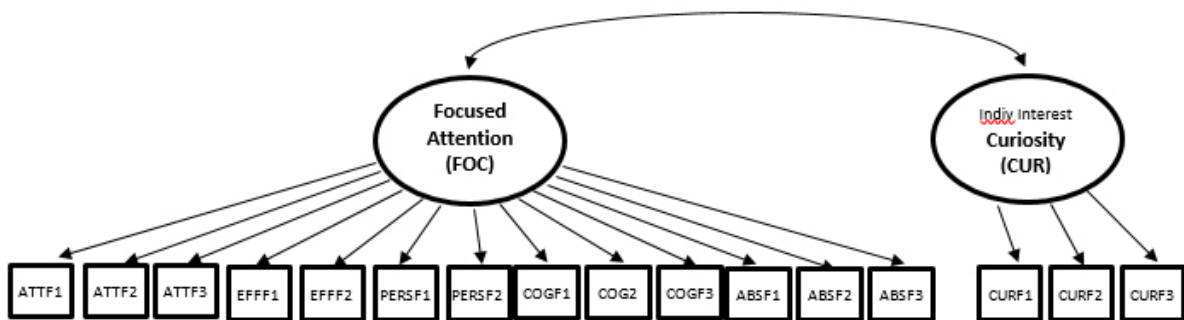
Figure 4. Face-to-Face CE Model 3, with two first order factors: focused attention (FOC) and curiosity (CUR).

However, Halverson and Graham, drawing upon the theory of flow (Csikszentmihalyi, 1990), argued that deep concentration or absorption and curiosity might be closely related. As

well, the highest factor intercorrelation for curiosity was with absorption (.851). For these

reasons, we tried one more variation of the model (CE Model 4 in Table 2). A factor we labeled

effort (EFF_F) was specified by attention, effort and persistence, and cognitive strategy use

indicators. A second factor, designated as *flow* (FLO_F), was specified by indicators of

absorption and curiosity (Figure 5). Results for this correlated two-factor model were similar to

those in CE Model 3: RMSEA = .083, CFI = .964, and TLI = .958. Indicators measured their

respective factors fairly well (.609 to .862 for EFF_F, .440 to .943 for FLO_F, $p < .001$). The

intercorrelation between face-to-face effort and flow was just barely above acceptable levels

$(0.852, p < 0.001)$.
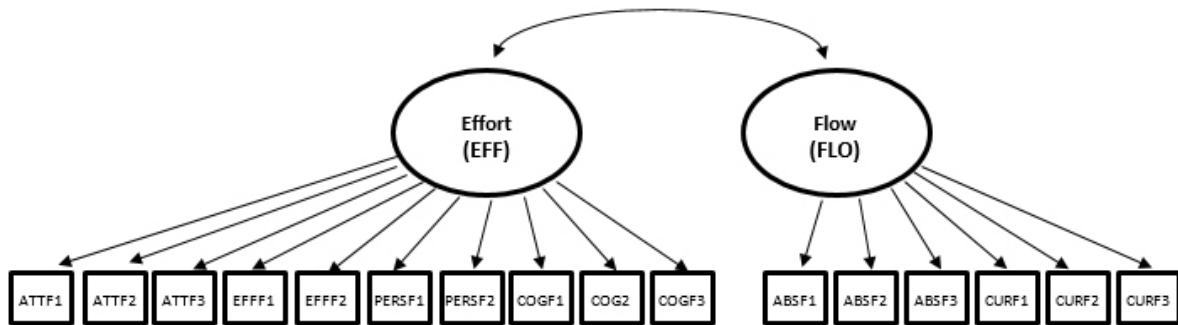
Figure 5. Face-to-Face CE Model 4, with two first order factors: effort (EFF) and flow (FLO).

Because of these high factor intercorrelations, we tested a one-factor model (CE Model 5

in Table 2) that might suggest that respondents perceived all items to belong to a unidimensional

construct (Figure 6). Model fit was less robust than either two-factor model (RMSEA = .102,

CFI = .946, TLI = .937), and we rejected the single-factor model. Since at least three indicators

are expected in order to have reliable latent constructs (Worthington & Whittaker, 2006), we did

not test a second order model of CE. A bifactor model did not achieve convergence.
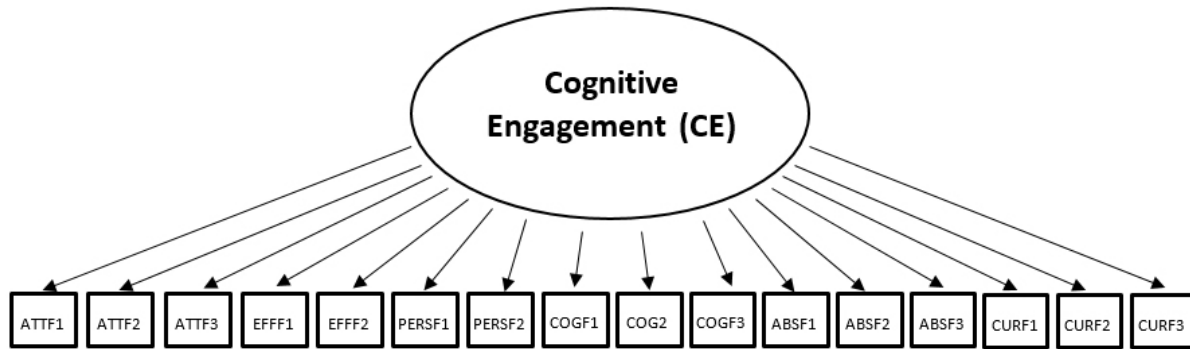
Figure 6. Face-to-Face CE Model 4, a single factor model in which all indicators load on CE.

Thus we had two comparable two-factor models, one with factors of focused attention and curiosity and another with factors of effort and flow. The intercorrelation between the factors of the latter model was higher than desirable, but we wondered whether introducing the online items might introduce differences.

Table 2

Summary of Goodness-of-Fit Indices for Alternative Models of Face-to-Face Cognitive

Engagement

Model	Goodness-of-Fit Measures			Comments
	CFI	TLI	RMSEA	
Optimal values	$> .950^a$	$> .950^b$	$< .060^c$	
CE Model 1 (Theoretical, without context factor)	.630	.591	.125	Context factor necessary
CE Model 2 (5 first order factors)	.977	.971	.069	Lacks discriminant validity
CE Model 3 (2 first order factors, FOC and CUR)	.952	.956	.085	Is curiosity an indicator or facilitator?
CE Model 4 (2 first order factors, EFF and FLO)	.964	.958	.083	$r = .852$ between EFF and FLO
CE Model 5 (single factor model)	.946	.937	.102	Rejected due to poor fit
CE Model 3a (Cross-validation of FOC and CUR)	.938	.931	.053	
CE Model 4a (Cross-validation of EFF and FLO)	.939	.931	0.053	

Note. CFI = comparative fit index; TLI = Tucker-Lewis index; RMSEA = root mean square error of approximation. [a] Hu and Bentler (1998, 1999). [b] Wang and Wang (2012). [c] Browne and Cudeck (1993), Byrne (2013), MacCallum, Browne, and Sugawara (1996).

Invariance testing across context. We next began to test whether the two-factor CE

models established using the face-to-face items would also apply to the online items.

Measurement invariance (also called measurement equivalence) is often used to determine

whether a particular measure is perceived in a conceptually similar manner by respondents from

different groups. In our case, we wanted to know whether online indicators and face-to-face

indicators of engagement were being interpreted as equivalent by respondents. Thus we

performed an analysis of measurement invariance to determine whether the face-to-face and

online items were comparable in factor loadings and estimated intercepts, and used the Satorra-

Bentler Scaled Chi-Square Difference Test to analyze the differences in chi-square and degrees

of freedom between the configural and weak measurement invariance models. Errors of similar

items were allowed to be correlated in these models due to the content similarities between face-

to-face and online items.

The online and face-to-face versions of CE Model 3 (focused attention and curiosity) had

configural invariance. Model fit was RMSEA = .053, CFI = .948, TLI = .941, χ^2 = 802.829 (df =

442). Weak measurement invariance across context was not achieved: The weak measurement

model including face-to-face and online factors had fit of RMSEA = .059, CFI = .933, TLI =

.928, χ^2 = 915.036 (df = 456). The resulting chi-square difference was 87.156 (df = 14, p < .001).

Similarly, the online and face-to-face versions of CE Model 4 (effort and flow) had configural

invariance. Model fit was RMSEA = .049, CFI = .955, TLI = .949, χ^2 = 753,551 (df = 442).

Once again weak measurement invariance across context was not achieved: The weak

measurement model including face-to-face and online factors had fit of RMSEA = .055, CFI =

.942, TLI = .937, χ^2 = 857.336 (df = 456). The resulting chi-square difference was 79.720 (df =

14, p < .001). The fact that neither model achieved weak measurement invariance suggests that

face-to-face engagement indicators are not equivalent to online engagement indicators. This

means that, for example, focused attention displayed in a face-to-face context is somehow

different than focused attention shown in an online one. Flow perceived in a face-to-face context

is likewise somehow different from flow perceived in an online setting.

Cross-validation. Once adequate model fit has been achieved, researchers recommend

cross-validation using a separate sample (Brown, 2006; Schumacker & Lomax, 2010). Both CE

models were cross-validated using data from the other half, which had been held back (n = 268).

Acceptable model fit was again achieved for both models. Fit for CE Model 3 (focused

attention, curiosity) was RMSEA = .053, CFI = .938, TLI = .931). The factor intercorrelations were acceptable: r = .780 between face-to-face curiosity and focused attention and .764 between online curiosity and focused attention. Table 3 displays the loadings and communalities of face-to-face and online items in this model, as well as the internal-consistency reliability measures (Cronbach's alpha) for each factor. Reliabilities were greater than the .70 benchmark suggested for modest composite reliability (Nunnally, 1978). Fit for CE Model 4 (effort, flow) was: RMSEA = .053, CFI = .939, TLI = .931. The factor intercorrelations were also acceptable: r = .847 between face-to-face flow and effort, and .823 between online flow and effort. Table 4 displays the loadings and communalities of both face-to-face and online items in CE Model 4, as well as Cronbach's alpha measures, all greater than .70. These results suggest that the two models fit the data comparably well; both will be further discussed hereafter. In both models, factors are differentiated by not only cognitive qualities, but also by context.

Table 3

Cross-Validation Factor Loadings of Cognitive Engagement Indicators: CE Model 3

Cognitive Engagement Indicators	Face-to-Face			Online		
	Loading	R^2	α	Loading	R^2	α
Focused Attention (FOC)			.876			.843
My mind wandered during F2F class/while completing OL assignments. (ATT1)[a]	.686	.471		.403	.162	
How often did you work on other things during F2F class time?/When I did OL work for this course, I multitasked. (ATT2)[a]	.619	.383		.463	.214	
Describe you level of attentiveness during F2F class/OL work for this course. (ATT3)	.850	.723		.614	.377	
Compared to other courses, the effort I put into F2F class activities/OL activities for this course has been: (EFF1)	.583	.339		.608	.370	
Even when F2F class/OL work for this course was uninteresting, I made an effort to learn. (EFF2)	.603	.364		.581	.338	
How persistent were you in trying to understand the material in F2F class/the material OL for this course? (PERS1)	.771	.595		.778	.605	
If I didn't understand something in F2F class, I listened more closely in order to better understand./ … something in OL work for this course, I kept working at it ... (PERS2)	.582	.339		.654	.428	
In F2F class/During OL instruction, I consciously tried to make the different ideas fit together and make sense in my mind. (COG1)	.549	.301		.626	.392	
How often did you take notes while in class/while reading or listening OL to help you understand what you were learning? (COG2)	.597	.356		.477	.227	
To what degree did you thoughtfully analyzed and evaluate the information presented in F2F class/OL instruction? (COG3)	.801	.641		.740	.547	
I became absorbed in F2F/OL learning activities for this course. (ABS1)	.713	.508		.706	.498	
How often did you lose track of time when in F2F class/when doing OL activities…? (ABS2)	.331	.110[b]		.383	.147	
Describe your level of absorption/deep concentration during F2F class/OL work…. (ABS3)	.863	.745		.776	.602	
Curiosity (CUR)			.777			.721
Something we discussed in F2F class/Something I read or watched OL for this course "stuck with me" and continues to be of interest to me. (CUR1)	.671	.450		.613	.376	
During F2F class/OL learning activities, my curiosity was piqued and I wanted to know more about principles and concepts being taught. (CUR2)	.839	.703		.748	.559	
Describe your level of curiosity during F2F class/OL work for this course. (CUR3)	.852	.726		.867	.752	

Note. Loadings are standardized estimates. All loading parameters are statistically significant at $p < 0.001$ (two-tailed) except for those indicated. [a] Item reverse scored. [b] $p < 0.01$

Table 4

Cross-Validation Factor Loadings of Cognitive Engagement Indicators: CE Model 4

Cognitive Engagement Indicators	Face-to-Face			Online		
	Loading	R^2	α	Loading	R^2	α
Effort (EFF)			.861			.802
My mind wandered during F2F class/while completing OL assignments. (ATT1)[a]	.694	.482		.403	.163	
How often did you work on other things during F2F class time?/When I did OL work for this course, I multitasked. (ATT2)[a]	.625	.390		.469	.220	
Describe you level of attentiveness during F2F class/OL work for this course. (ATT3)	.869	.756		.615	.379	
Compared to other courses, the effort I put into F2F class activities/OL activities for this course has been: (EFF1)	.591	.349		.613	.375	
Even when F2F class/OL work for this course was uninteresting, I made an effort to learn. (EFF2)	.610	.372		.588	.345	
How persistent were you in trying to understand the material in F2F class/the material OL for this course? (PERS1)	.781	.610		.787	.620	
If I didn't understand something in F2F class, I listened more closely…/ If I didn't understand something in OL work for this course, I kept working at it until I thought I'd solved it. (PERS2)	.590	.348		.664	.441	
In F2F class/During OL instruction, I consciously tried to make the different ideas fit together and make sense in my mind. (COG1)	.559	.312		.634	.402	
How often did you take notes while in class/while reading or listening OL to help you understand what you were learning? (COG2)	.603	.363		.479	.229	
To what degree did you thoughtfully analyzed and evaluate the information presented in F2F class/OL instruction? (COG3)	.811	.658		.749	.560	
Flow (FLO)			.808			.794
I became absorbed in F2F/OL learning activities for this course. (ABS1)	.732	.535		.762	.580	
How often did you lose track of time when in F2F class/when doing OL activities…? (ABS2)	.349	.122[b]		.426	.181	
Describe your level of absorption/deep concentration during F2F class/OL work.... (ABS3)	.920	.846		.836	.699	
Something we discussed in F2F class/Something I read or watched OL for this course "stuck with me" and continues to be of interest to me. (CUR1)	.624	.389		.564	.318	
During F2F class/OL learning activities, my curiosity was piqued and I wanted to know more about principles and concepts being taught. (CUR2)	.766	.587		.694	.481	
Describe your level of curiosity during F2F class/OL work for this course. (CUR3)	.765	.586		.769	.592	

Note. Loadings are standardized estimates. All loading parameters are statistically significant at $p < 0.001$ (two-tailed) except for those indicated. [a] Item reverse scored. [b] $p < 0.01$

Emotional Engagement

Halverson and Graham (under review) proposed that EE is composed of positive energy indicators, including *interest and enjoyment, happiness*, and *confidence*, while negative energy indicators include *boredom, frustration*, and *anxiety*. They also suggested investigating the first order factor of *confusion;* depending on the learner's feelings about the activity, confusion may indicate positive or negative energy. Seeking good model fit with constructs showing convergent and discriminant validity, we tested three models, explained in further detail below. Our first model, EE Model 1, was based on Halverson and Graham's theoretical constructs and did not separate indicators by context, but this had poor model fit. A subsequent EFA showed that, as was the case with CE, context was the clearest element in factor structure. As was done with CE, we chose to test face-to-face indicators only, select the best-fitting models, and then use invariance testing across context to determine whether the online indicators were comparable. We tested a seven-factor model based on the theoretical first order factors (EE Model 2). Model fit was good, but several factors lacked discriminant validity. We respecified the models to take these factor intercorrelations into account, and then tested a three-factor model featuring the constructs of positive emotional engagement, negative emotional engagement, and confidence (EE Model 3), which showed good model fit.

Initial confirmatory factor analysis. As we did in testing CE, we chose to run an initial CFA ($n = 549$) based on the EE model proposed by Halverson and Graham's theoretical framework (EE Model 1 in Table 5). Again we ran this CFA without the context condition, allowing all items purported to measure an indicator like enjoyment to be grouped under the first order construct enjoyment, without divisions into *online enjoyment* and *face-to-face enjoyment*. All the positive first order constructs were then specified to measure a second order factor,

positive emotional engagement (POS), and the negative first order constructs were specified to measure the second order factor *negative emotional engagement* (NEG). The model was estimated using WLSMV with categorical indicators. Again we compared factor loadings estimated using WLSMV and MLR and found similar results, suggesting that there was no method effect and that any missing data were missing completely at random (MCAR).

All items measured the first order constructs well (standardized loadings ranging from .534 to .922; $p < .001$). The differences in measurement sensitivity between paired face-to-face and online results were not as striking as in CE. For example, the loadings of indicator ENJ_F1 on the latent variable enjoyment (ENJ) was .849, while the online item ENJ_O1 loaded at .811. At the second order level, enjoyment, happiness, and confidence loaded well on POS (.910, .906, .719, respectively; $p < .001$), while boredom, frustration, and anxiety loaded well on NEG (.820, .914, .684 respectively; $p < .001$). The correlation between confusion and POS was -.522, while the correlation between confusion and NEG was .850. Finally NEG and POS were significantly correlated ($r = -.867, p < .001$). Overall model fit was poor: RMSEA = .158, CFI = .636, TLI = .615, $\chi^2 = 13071.235$ ($df = 893$), suggesting that this model needed modifying.

Exploratory factor analysis. To search for a better fitting model, we conducted another EFA of the 44 emotional engagement items with the same approach used for CE. We again used Bartlett's test of sphericity to discern the factorability of the data and the KMO test to determine the sampling adequacy. Results indicated that the data were suitable for factor detection (Bartlett's test of sphericity: χ^2 (946) = 9278.820, p < 0.001; KMO = 0.915). This suggested six factors with eigenvalues over 1.0. A scree plot inspection suggested four or six factors.

The six-factor model lacked interpretability, but the four-factor model gave us insights into some possible model revisions. First, confusion loaded much more strongly on NEG than

on POS. Second, a new cluster of items emerged, as all of the boredom indicators and one

frustration indicator (FRUS2)—items which seemed to express a sense of detachment from the

learning experience—had high negative loadings onto POS, rather than loading onto NEG as

Halverson and Graham (under review) had theorized. We reverse-scored the items and labeled

this factor *lack of detachment* (DET). Most striking was that, as with CE, context was

unambiguously important in factor structure. *Face-to-face positive emotional engagement*

(POS_F) was reflected by face-to-face enjoyment (ENJ_F), happiness (HAP_F), lack of

detachment (DET_F), and one confidence (CONFD_F) item. *Online positive emotional*

engagement (POS_O) was similarly comprised but was reflected by all online confidence

(CONFD_O) items. *Face-to-face negative emotional engagement* (NEG_F) was reflected by

face-to-face anxiety (ANX_F), confusion (CONFS_F), and the remaining frustration (FRUS_F)

indicators. In addition, all face-to-face confidence (CONFD_F) items loaded negatively to this

factor. *Online negative emotional engagement* (NEG_O) was reflected by online anxiety

(ANX_O), confusion (CONFS_O), and the remaining frustration (FRUS_O) indicators, but

online confidence (CONFD_O) items did not reflect NEG_O. Overall, online items reflecting

the factor confidence matched Halverson and Graham's (under review) theoretical model by

loading onto POS_O (.411-.560, $p < .001$), with lower but significant loadings onto NEG_F.

However the face-to-face confidence items had a unique pattern, loading onto NEG_F (-.759 to -

.768, $p < .001$).

      We determined to test a few different CFAs, including the factor of detachment, aligning

confusion with NEG, and trying various models that retained, double-loaded, or dropped the

confidence items. Our models first tested the face-to-face emotional engagement items alone,

and then tested whether the online items follow the same model suggested.

Confirmatory factor analysis of face-to-face EE items. Employing the same sample half utilized in the EFAs, we conducted several CFAs. A first order CFA (EE Model 2 in Table 5) was conducted to include a lack of detachment factor (Figure 7). Results for this correlated seven-factor EE model suggested good fit: RMSEA = .058, CFI = .986, TLI = .983. All indicators measured their respective factors well (.679-.946, $p < .001$). All indicators now specified on lack of detachment had high standardized parameter estimates, ranging from .844 to .946. Lack of detachment correlated particularly strongly with enjoyment (.928) and happiness (.852), while confusion correlated particularly strongly with frustration (.818), anxiety (.889), and a (lack of) confidence (-.853). These high factor intercorrelations suggested that some of our first order factors lacked discriminant validity.
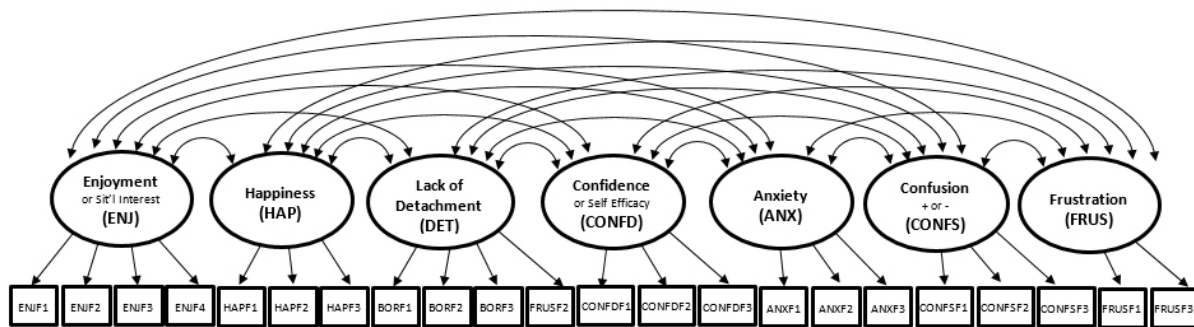
Figure 7. Face-to-Face EE Model 2, with seven first order factors: enjoyment or situational interest, happiness, lack of detachment, confidence, anxiety, confusion, and frustration.

Our next step was to hypothesize a correlated three-factor EE measurement model (EE Model 3 in Table 5). *Positive emotional engagement* (POS_F) was specified by enjoyment, happiness, and lack of detachment indicators. *Negative emotional engagement* (NEG_F) was specified by anxiety, confusion, and frustration indicators. Because we found that confidence had a unique pattern across contexts (POS_O being specified by CONFD_O, but NEG_F being specified by CONFD_F), we chose to keep confidence as a unique factor in this model (see

Figure 8). Results suggested acceptable fit: RMSEA = .090, CFI = .964, and TLI = .960.

Indicators measured their respective factors fairly well (.785 to .919 for POS_F, .744 to .890 for

NEG_F, and .675 to .819 for CONFD_F, $p < .001$), showing convergent validity. Supporting

discriminant validity, no factor intercorrelations also surpassed .850 ($r = .397$ between

CONFD_F and POS_F; -0291 between NEG_F and POS_F; and -.820 between NEG_F and

CONFD_F, $p < .001$).
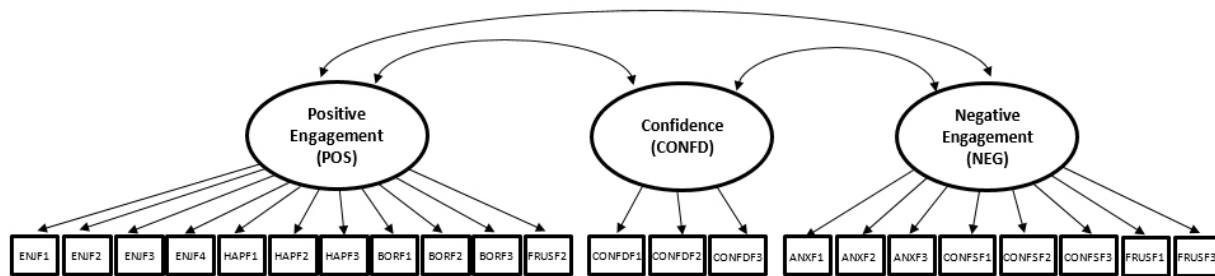
Figure 8. Face-to-Face EE Model 3, with three first order factors: positive engagement (POS),
confidence (CONFD), and negative engagement (NEG).

Because of the multifaceted nature of emotional engagement (particularly negative

engagement or disaffection, according to Skinner, Kindermann, & Furrer, 2009), we did not

expect a second order model to have good fit, and we achieved no convergence when we tested a

model with the superfactor of emotional engagement, comprised of face-to-face positive

engagement, confidence, and negative engagement.

Table 5

Summary of Goodness-of-Fit Indices for Alternative Models of Face-to-Face Emotional

Engagement

Model	Goodness-of-Fit Measures			Comments
	CFI	TLI	RMSEA	
Optimal values	> .950[a]	> .950[b]	< .060[c]	
EE Model 1 (Theoretical, without context factor)	.158	.636	.615	Context factor necessary
EE Model 2 (7 first order factors)	.986	.983	.058	Lacks discriminant validity
CE Model 3 (3 first order factors, POS, NEG, CONFD)	.964	.960	.090	Good fit and discriminant validity
CE Model 3a (Cross-Validation)	.967	.963	.048	

Note. CFI = comparative fit index; TLI = Tucker-Lewis index; RMSEA = root mean square error of approximation. [a] Hu and Bentler (1998, 1999). [b] Wang and Wang (2012). [c] Browne and Cudeck (1993), Byrne (2013), MacCallum, Browne, and Sugawara (1996).

Invariance testing across context. Having established a model using the face-to-face emotional engagement items, we tested its comparability to the online data. We conducted an invariance test between the face-to-face and online models; again, errors of similar items were allowed to be correlated in these models due to the content similarities between face-to-face and online items. The face-to-face and online models showed configural invariance (RMSEA = 0.052, CFI = 0.962, TLI = 0.958) but did not display weak measurement invariance. As we found in examining cognitive engagement, these findings suggest that positive emotional engagement (for example) indicated in a face-to-face context is somehow different than positive emotional engagement indicated in an online one.

Cross-validation. The EE model established using approximately half of our sample was cross-validated using data from the other half which had been held back ($n = 263$). Good model fit was again achieved (RMSEA = 0.048, CFI = 0.967, TLI = 0.963). The standardized estimates for all indicators ranged from 0.633 to 0.896, showing good convergent validity, and

the factor intercorrelations ranged from .028 (POS_F with NEG_O) to -.816 (NEG_F with

CONFD_F). Table 6 displays the loadings and communalities of both face-to-face and online

items, as well as Cronbach's alpha for each factor. Reliabilities for face-to-face and online POS

and NEG were *excellent*, while those for face-to-face and online confidence were *adequate*.

These results provided support for a hierarchical model of EE, including factors of positive

emotional engagement (such as enjoyment, happiness, and a feeling of attachment), negative

emotional engagement (frustration, anxiety, and confusion), and confidence. These factors were

perceived in face-to-face and online contexts, though they were not equivalent across contexts.

Table 6

Cross Validation Factor Loadings of Emotional Engagement Indicators: EE Model 3

Emotional Engagement Indicators	Face-to-Face			Online		
	Loading	R^2	α	Loading	R^2	α
Positive Emotional Engagement			.949			.919
I enjoyed the F2F time I spend in this class./I enjoyed the OL activities for this course. (ENJ1)	.893	.797		.849	.721	
How interesting was the material covered in F2F class/OL work for this course? (ENJ2)	.789	.622		.744	.553	
Describe your level of interest during F2F class/OL work for this course. (ENJ3)	.849	.721		.841	.708	
I look forward to going to F2F class/OL learning activities for this course. (ENJ4)	.863	.744		.810	.656	
I felt happy during F2F/OL learning activities. (HAP1)	.750	.562		.756	.571	
To what extent did you feel glad during F2F class/OL learning activities? (HAP2)	.885	.783		.795	.632	
Describe your level of happiness during F2F class/OL work for this course. (HAP3)	.887	.787		.816	.665	
F2F class was dull./The OL materials for this course were dull. (BORE1) [a]	.876	.767		.776	.602	
When in F2F class/During OL activities for this course, I felt bored. (BORE2) [a]	.804	.647		.712	.508	
Describe your level of boredom during F2F class/OL work for this course. (BORE3) [a]	.878	.772		.728	.531	
How often did you feel like sitting in class/OL work for this course was a waste of your time? (FRUS2) [a]	.803	.644		.665	.443	
Confidence / Self-efficacy			.741			.715
How confident did you feel that you could understand the most difficult materials …? (CONFD1)	.713	.508		.766	.586	
How confident did you feel that you could understand the basic concepts …? (CONFD2)	.674	.454		.633	.401	
After attending F2F class/completing OL activities, I felt confident about my ability to succeed in this course. (CONFD3)	.856	.732		.768	.590	
Negative Emotional Engagement			.921			.899
To what extent did you feel frustrated while in class/during OL work for the course? (FRUS1)	.888	.789		.896	.803	
Describe your level of frustration during F2F class/during OL work for this course. (FRUS3)	.868	.753		.867	.752	
F2F class/OL work for this course stressed me out. (ANX1)	.716	.513		.647	.419	
How worried did you feel while in F2F class/during OL work for this course? (ANX2)	.823	.678		.737	.543	
Describe your level of anxiety during F2F class/OL work for this course. (ANX3)	.738	.545		.727	.529	
I felt confused during F2F class/while doing OL assignments for this course. (CONFS1)	.789	.623		.724	.524	
I felt puzzled in F2F class/while doing OL assignments for this course. (CONFS2)	.840	.706		.718	.515	
Describe your level of confusion during F2F class/OL work for this course. (CONFS3)	.863	.744		.853	.727	

Note. Loadings are standardized estimates. All loading parameters are statistically significant at $p < 0.001$ (two-tailed) except for those indicated. [a] Item reverse scored.

Discussion

The purpose of this study was to operationalize and test a proposed model of blended learning engagement using exploratory and confirmatory factor analysis. Although learner engagement has been described as "the holy grail of learning" (Sinatra, Heddy, & Lombardi, 2015, p. 1) due to its correlations with student satisfaction, achievement, and persistence, the constructs and definitions of learner engagement are ill-conceived in general and even less understood in blended contexts. We selected a theoretical framework for learner engagement (Halverson & Graham, under review) and subjected it to exploratory and confirmatory factor analyses, invariance testing across contexts, and cross-validation in order to determine the strength of the model of engagement.

One of the clearest conclusions from our research is the related but nevertheless distinct nature of face-to-face and online engagement. EFAs unambiguously showed that context matters in the factor structure development. We achieved configural invariance across contexts when testing the CE and EE models, showing that the same structure applies to both contexts and that the paired questions held together in a pattern though not at the same level of strengths. However, we did not achieve weak or strong measurement invariance across contexts. Particularly within cognitive engagement, factor loadings of paired face-to-face and online items behaved quite uniquely. These discrepancies were apparent in the analyses of emotional engagement as well, though less pronounced. Overall, our data showed that measures of engagement must be context-specific.

We were surprised that differences between online and face-to-face indicators would be stronger than all other differences. It is possible that the differences indicate that learners have a harder time understanding what engagement means in the online setting. Alternatively, perhaps

their online experiences were perceived as more varied than their face-to-face class experiences.

Finally, the paired questions were presented together in the survey, and the face-to-face items

always presented first. This could have introduced an order effect into the results.

However, other explanations may also help account for our finding. If pedagogical

methods differ across modality, is what we are seeing less an effect of modality and more an

effect of pedagogy? If learners experience engagement differently based on pedagogy, then the

best level at which to measure engagement is the activity level, where the effect of different face-

to-face and different online activities on engagement can be evaluated. Because we wished our

framework to be generalizable, we intentionally collected data from many different courses

displaying variation in blended course design. However, if the observed "context effect" is

actually due to pedagogy, research will need to look at specific pedagogies in specific classes,

making the large data sets required for factor analysis more difficult to collect. More research

into "the actual experience of an activity or event" (Davis & McPartland, 2012, p. 516) can be

done to explore the differences that various pedagogies have on cognitive and emotional energy.

Another significant finding was the empirical equivalence between indicators that some

models separate into cognitive and behavioral categories. Halverson and Graham's (under

review) framework suggested that cognitive engagement was comprised of several first order

constructs—attention, effort and persistence, time on task, cognitive strategy use, absorption, and

curiosity—some of which have been considered behavioral in other models of learner

engagement. Halverson and Graham argued "that what other models are considering displays of

behavioral engagement are actually indicators of underlying cognitive and emotional

involvement" and are "outward displays of the mental and emotional energies that fuel learning."

They proposed that attention, effort and persistence, and time on task might indicate quantity of

CE, while cognitive strategy use, absorption, and curiosity might indicate CE quality. Although

our analysis had to drop the time on task variable due to issues in the way we operationalized the

construct, in a model not presented here we found that second order quantity and quality factors

could not be justified because they were so highly correlated ($r = .977$) that the constructs were

empirically indistinguishable. At the first order level, cognitive strategy use (the hallmark of CE

in most other frameworks) and effort and persistence (usually considered aspects of behavioral

engagement) were likewise empirically equivalent ($r = .994$). This sheds light upon the

longstanding theoretical debate as to the nature of cognitive engagement (Pintrich & DeGroot,

1990; Zimmerman, 2002) and gives justification to Halverson and Graham's assertion that certain

behavioral manifestations of engagement are best conceptualized as expressions of the internal

processes of CE.

We presented two different two-factor models of CE for consideration. In one (CE Model

3), focused attention was specified by attention, effort and persistence, cognitive strategy use, and

absorption indicators; the second factor was curiosity. Since curiosity was the factor most unique

from the other factors, a single-factor model in which curiosity is better regarded as a *facilitator*

of engagement might be also investigated in future research. As Skinner, Furrer, Marchand, and

Kindermann (2008) have written, "Indicators refer to the features that belong inside the construct

of engagement proper, whereas facilitators are the causal factors (outside of the construct) that are

hypothesized to influence engagement" (p. 766). In a second model (CE Model 4), effort was

specified by attention, effort and persistence, cognitive strategy use indicators, and flow was

specified by absorption and curiosity indicators. Since absorption and curiosity seem to us to be

integral to deep engagement, we find this the more compelling of the two models. However, one

absorption item pair (ABS2: How often did you lose track of time when in face-to-face

class/when doing online activities for this course?) was the weakest measure of CE in our scale. Replacing this item might increase reliability. This question was particularly intended to measure a state of flow, so if researchers are interested in CE Model 4, refining these indicators to more clearly measure deep absorption and the state of flow would be important.

Our preferred EE Model (EE Model 3) measured constructs in ways unique from the original framework proposed by Halverson and Graham (under review) and from the models of Skinner and colleagues upon which Halverson and Graham largely based their concept of negative EE. Skinner and colleagues saw positive EE as primarily about enjoyment and interest; Halverson and Graham proposed including happiness and confidence as well. Skinner and colleagues found evidence for a hierarchical model of negative EE, comprised of boredom, frustration, and anxiety; Halverson and Graham adopted this construct. Confusion was not included in the emotional disaffection model proposed by Skinner and colleagues, but as the second-most frequent affective state in technology-mediated learning contexts (D'Mello, 2013), Halverson and Graham suggested additional research to better understand its role in blended learning engagement.

Our findings rearranged some of these alliances. First, we found that confusion, at least when recalled in an end-of-course survey (thus considerably after any particular learning activity), is remembered by learners as negative. This does not contradict other assertions that confusion during the moment of a learning activity in which the learner is engaged and interested may spur on investigation and thus learning (Baker et al., 2010; D'Mello et al., 2014). D'Mello et al. (2014) state that "one important form of deep learning occurs when there is a discrepancy in the information stream and the discrepancy is identified and corrected," a kind of confusion they call "productive" (p. 155). It is possible that learners do not later remember this temporary state

as confusion, but only recall those frustrating unresolved impasses under that label. This suggests that those who wish to research confusion in technology-mediated settings will need to take into account not only the accompanying emotions (e.g., boredom, frustration, or interest) but also whether the instrument is measuring confusion felt in the moment of a learning activity or recalled at a later date. Once again, context is critical in measuring indicators of engagement.

Next our findings suggested that detachment indicators correlated most strongly (and negatively) with happiness and enjoyment, rather than with the other negative emotions of frustration, anxiety, and confusion. Detachment contained items inquiring into perceived boredom as well as one item which we had intended to measure frustration: "How often did you feel like sitting in class/like online work for this course was a waste of your time?" This constellation of items seemed to crystallize around the very absence of interest, enjoyment, and happiness. In circumplex models of emotion, the latter have been described as *positive activating emotions*, while boredom and detachment are their orthogonal opposites, *negative deactivating emotions* (Feldman Barrett & Russell, 1998; Pekrun & Linnenbrink-Garcia, 2012). Frustration and anxiety have been classified as *negative activating emotions*, and had high enough factor intercorrelations to justify consolidation, along with confusion, into a single variable of negative EE. Because we have utilized a definition of learner engagement as the investment of cognitive and emotional energy to bring about a learning task, physiological activation and deactivation ought to be considered for their impact upon emotional energy. It is possible that activating emotions (positive or negative) are stronger indicators of engagement than deactivating ones; effects of the presence of activating and deactivating emotional states on the overall learning process might thus be questioned. Perhaps the construct we have called POS might better be labeled energy-producing emotions (enjoyment, happiness, and attachment), while the construct

we have labeled NEG might be better viewed as energy-depleting emotions (frustration, anxiety, and confusion).

Context was again important in measuring confidence. Indicators from the confidence variable behaved uniquely across context. The EFAs showed that online confidence indicators loaded as Halverson and Graham (under review) had expected, aligning with the other online POS factors such as enjoyment and happiness (though with significant double-loadings on other factors as well). Face-to-face confidence, in contrast, had high negative loadings onto face-to-face NEG. Halverson and Graham noted that confidence might function as both a facilitator and an indicator of engagement. Longitudinal research could help establish whether confidence primarily precedes and facilitates engagement instead of indicating an engaged state. Due to the difficulties we experienced with this factor, future research might consider dropping it from the model of engagement indicators.

Future research can further refine the scale utilized in this research. Since our findings suggest that online and face-to-face engagement are unique constructs, perhaps our careful pairing of items was unnecessary. We felt restrained in dropping items when a weak item (such as ATT_O1, "My mind wandered while completing online assignments") had a stronger partner (ATT_F1, "My mind wandered during face-to-face class"). Perhaps face-to-face confidence, for example, ought to be measured in ways unique from the measurement of online confidence. If proceeding with CE Model 4, we need better measures of the perception of flow; our face-to-face question most intended to investigate this state was the weakest CE indicator. Finally, time on task might be reintroduced into the CE model if better operationalized.

We utilized an end-of-course survey in this research, attempting to measure course-level engagement. However, engagement may be "fundamentally situational" (Kahu, 2013, p. 763). If

this is true, then activity-level measures of engagement (such as Henrie, Larsen, Manwaring, Halverson, & Graham, under review) will give us the best information about how different face-to-face and online experiences impact learner engagement in blended courses. As we have noted already, confusion measured at the end of a course was recalled negatively, but confusion in the moment of a learning activity may if accompanied by interest and curiosity actually spur learner engagement, investigation, and learning.

In conclusion, developing and testing this new instrument has offered important insights to our understanding of blended learning engagement. First, context matters in how learners perceive their own engagement in settings that combine face-to-face and technology-mediated learning activities. Whether this is more a reflection of modality or of pedagogy requires further research, especially at the activity level. Second, factors that some models label behavioral are empirically indistinguishable from those considered cognitive; thus the behavior and cognitive engagement models can be combined as one and the underlying construct—cognitive engagement—considered the root of behavioral manifestations of learner engagement. We recommend a model of cognitive engagement that considers effort (attention, persistence, effort, and cognitive strategy use) as well as flow (curiosity and absorption). Learner's emotional energy can be positive or negative, with the latter consuming rather than fueling cognitive resources for learning. These findings can inform how we conceptualize and measure engagement in blended settings. Improved measures of engagement, it follows, will allow us to better assess which combinations of face to face and computer-mediated technologies are truly "the best of both worlds" (Bele & Rugeli, 2007).

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Appendix

Blended Learning Course Engagement Survey

1A. My mind wandered during face-to-face class.
      a. Never b. Rarely   c. Sometimes   d. Often   e. All the time
1B. My mind wandered while completing online assignments.
      a. Never b. Rarely   c. Sometimes   d. Often   e. All the time

2A. Something we discussed in face-to-face class "stuck with me" and continues to be of interest to me.
      a. Never b. Rarely   c. Sometimes   d. Often   e. All the time
2B. Something I read or watched online for this course "stuck with me" and continues to be of interest to me.
      a. Never b. Rarely   c. Sometimes   d. Often   e. All the time

3A. I felt confused in face-to-face class.
      a. Never b. Rarely   c. Sometimes   d. Often   e. All the time
3B. I felt confused while doing the online assignments for this course.
      a. Never b. Rarely   c. Sometimes   d. Often   e. All the time

4A. Compared to other courses, the effort I put into **face-to-face class activities** has been:
    a.   Extremely low (probably the least amount of effort I've ever put into a class)
    b.   Low
    c.   About average
    d.   High
    e.   Extremely high (probably as much effort as I've ever put into a class)
4B. Compared to other courses, the effort I put into **online activities for this course** has been:
    a.   Extremely low (probably the least amount of effort I've ever put into a course)
    b.   Low
    c.   About average
    d.   High
    e.   Extremely high (probably as much effort as I've ever put into a course)

5A. When in face-to-face class, I felt bored.
      a. Never b. Rarely   c. Sometimes   d. Often   e. All the time
5B. During online activities for this course, I felt bored.
      a. Never b. Rarely   c. Sometimes   d. Often   e. All the time

6A. During face-to-face class, I consciously tried to make the different ideas fit together and make sense in my mind.

   a. Never b. Rarely   c. Sometimes   d. Often   e. All the time

6B. During online instruction, I consciously tried to make the different ideas fit together and make sense in my mind.

   a. Never b. Rarely   c. Sometimes   d. Often   e. All the time

7A. I felt happy during face-to-face learning activities.

   a. Never b. Rarely   c. Sometimes   d. Often   e. All the time

7B. I felt happy during online learning activities.

   a. Never b. Rarely   c. Sometimes   d. Often   e. All the time

8A. I became absorbed in face-to-face learning activities for this course.

   a. Not at all absorbed   b. Not very absorbed   c. Moderately absorbed

   d. Quite absorbed   e. Extremely absorbed

8B. I became absorbed in online learning activities for this course.

   b. Not at all absorbed   b. Not very absorbed   c. Moderately absorbed

   e. Quite absorbed   e. Extremely absorbed

9A. Face-to-face class stressed me out.

   a. Never b. Rarely   c. Sometimes   d. Often   e. All the time

9B. Online work for this course stressed me out.

   a. Never b. Rarely   c. Sometimes   d. Often   e. All the time

10A. After attending face-to-face class, I felt confident about my ability to succeed in this course.

   a. Never b. Rarely   c. Sometimes   d. Often   e. All the time

10B. After completing online activities, I felt confident about my ability to succeed in this course.

   a. Never b. Rarely   c. Sometimes   d. Often   e. All the time

11A. During face-to-face class, my curiosity was piqued and I wanted to know more about principles and concepts being taught.

   a. Never b. Rarely   c. Sometimes   d. Often   e. All the time

11B. During online learning activities, my curiosity was piqued and I wanted to know more about principles and concepts being taught.

   a. Never b. Rarely   c. Sometimes   d. Often   e. All the time

12A. Even when the face-to-face class was uninteresting, I made an effort to learn.

    a. Never b. Rarely   c. Sometimes   d. Often   e. All the time

12B. Even when the online work for this course was uninteresting, I made an effort to learn.

    a. Never b. Rarely   c. Sometimes   d. Often   e. All the time

13A. I looked forward to going to face-to-face class.

    a. Never b. Rarely   c. Sometimes   d. Often   e. All the time

13B. I looked forward to online learning activities for this course.

    a. Never b. Rarely   c. Sometimes   d. Often   e. All the time

14A. If I didn't understand something in face-to-face class, I listened more closely in order to better understand.

    a. Never b. Rarely   c. Sometimes   d. Often   e. All the time

14B: If I didn't understand something in online work for this course, I kept working at it until I thought I'd solved it.

    a. Never b. Rarely   c. Sometimes   d. Often   e. All the time

*15A. Face-to-face time in class challenged me to do my best work.

    a. Never b. Rarely   c. Sometimes   d. Often   e. All the time

*15B. Online requirements for this course challenged me to do my best work.

    a. Never b. Rarely   c. Sometimes   d. Often   e. All the time

16A. I felt puzzled in face-to-face class.

    a. Never b. Rarely   c. Sometimes   d. Often   e. All the time

16B. I felt puzzled while doing online assignments for this course.

    a. Never b. Rarely   c. Sometimes   d. Often   e. All the time

17A. I enjoyed the face-to-face time I spent in this class.

    a. Never b. Rarely   c. Sometimes   d. Often   e. All the time

17B. I enjoyed the online activities for this course.

    a. Never b. Rarely   c. Sometimes   d. Often   e. All the time

18A. How confident did you feel that you could understand the most difficult material presented in face-to-face class?

    a. Not at all confident   b. Not very confident   c. Moderately confident
    f. Quite confident   e. Extremely confident

18B. How confident did you feel that you could learn the most difficult course material presented online?

    a. Not at all confident   b. Not very confident   c. Moderately confident

        d. Quite confident   e. Extremely confident

*19A. How relevant to your life is what you learned in face-to-face class?

        a. Not at all relevant   b. Not very relevant   c. Moderately relevant

        d. Quite relevant   e. Extremely relevant

*19B. How relevant to your life is what you learned in online work for this course?

        a. Not at all relevant   b. Not very relevant   c. Moderately relevant

        d. Quite relevant   e. Extremely relevant

20A. How interesting was the material covered in face-to-face class?

        a. Not at all interesting b. Not very interesting   c. Moderately interesting

        g. Quite interesting   e. Extremely interesting

20A. How interesting was the material covered in online work for this course?

        a. Not at all interesting b. Not very interesting   c. Moderately interesting

        d. Quite interesting   e. Extremely interesting

*21A. How challenged were you by the face-to-face class material?

        a. Not at all challenged b. Not very challenged   c. Moderately challenged

        d. Quite challenged   e. Extremely challenged

*21B. How challenged were you by the online work for this course?

        a. Not at all challenged b. Not very challenged   c. Moderately challenged

        d. Quite challenged   e. Extremely challenged

22A. How often did you lose track of time when in face-to-face class?

        a. Never b. Rarely   c. Sometimes   d. Often   e. All the time

22B. How often did you lose track of time when doing online activities for this course?

        a. Never b. Rarely   c. Sometimes   d. Often   e. All the time

23A. To what extent did you feel frustrated while in class?

        a. Not at all frustrated b. Not very frustrated   c. Moderately frustrated

        d. Quite frustrated   e. Extremely frustrated

23B. To what extent did you feel frustrated during the online work for the course?

        a. Not at all frustrated b. Not very frustrated   c. Moderately frustrated

        d. Quite frustrated   e. Extremely frustrated

24A. How often did you take notes while in class to help you understand what you were learning?

        a. Never b. Rarely   c. Sometimes   d. Often   e. All the time

24B. How often did you take notes while reading or listening online to help you understand what you were learning?

        a. Never b. Rarely   c. Sometimes   d. Often   e. All the time

25A. How often did you feel like sitting in class was a waste of your time?

        a. Never b. Rarely   c. Sometimes   d. Often   e. All the time

25B. How often did you feel like online work for this course was a waste of your time?

        a. Never b. Rarely   c. Sometimes   d. Often   e. All the time

26A. To what extent did you feel glad during face-to-face class?

        a. Not at all glad   b. Not very glad   c. Moderately glad

        d. Quite glad   e. Extremely glad

26B. To what extent did you feel glad during online learning activities?

        a. Not at all glad   b. Not very glad   c. Moderately glad

        d. Quite glad   e. Extremely glad

27A. How often did you work on other things during face-to-face class time?

        a. Never b. Rarely   c. Sometimes   d. Often   e. All the time

27B. How often did you multitask on other screens while completing the online work for this course?

        a. Never b. Rarely   c. Sometimes   d. Often   e. All the time

28A. How persistent were you in trying to understand the material in face-to-face class?

        a. Not at all persistent b. Not very persistent   c. Moderately persistent

        d. Quite persistent   e. Extremely persistent

28B. How persistent were you in trying to understand the material online for this course?

        a. Not at all persistent b. Not very persistent   c. Moderately persistent

        d. Quite persistent   e. Extremely persistent

29A. How worried did you feel while in face-to-face class?

        a. Not at all worried   b. Not very worried   c. Moderately worried

        d. Quite worried   e. Extremely worried

29B. How worried did you feel during online work for this course?

        a. Not at all worried   b. Not very worried   c. Moderately worried

        d. Quite worried   e. Extremely worried

30A. To what degree did you thoughtfully analyze and evaluate the information presented in face-to-face class?

        a. Not at all thoughtfully b. Not very thoughtfully   c. Moderately thoughtfully

        d. Quite thoughtfully   e. Extremely thoughtfully

30B. To what degree did you thoughtfully analyze and evaluate the information presented in online instruction?

        a. Not at all thoughtfully b. Not very thoughtfully   c. Moderately thoughtfully

        d. Quite thoughtfully   e. Extremely thoughtfully

31A. Face-to-face class was dull.
        a. Never b. Rarely   c. Sometimes   d. Often   e. All the time

31B. The online materials for this course were dull.
        a. Never b. Rarely   c. Sometimes   d. Often   e. All the time

32A. How confident did you feel that you could understand the basic concepts presented in face-to-face class?
        a. Not at all confident   b. Not very confident   c. Moderately confident
        d.   Quite confident   e. Extremely confident

32B. How confident did you feel that you could understand the basic concepts presented online?
        a. Not at all confident   b. Not very confident   c. Moderately confident
        d.   Quite confident   e. Extremely confident

33A. In an average week, how much time did you spend **in class** for this course?
        a. 0 – 60 minutes
        b. 61 – 120 minutes
        c. 121 – 180 minutes
        d. 181 – 240 minutes
        e. More than 4 hours

33B. In an average week, how much time did you spend **in online activities** for this course?
        a. 0 – 60 minutes
        b. 61 – 120 minutes
        c. 121 – 180 minutes
        d. 181 – 240 minutes
        e. More than 4 hours

34A. Describe your level of attentiveness during face-to-face class.
        a. Not at all attentive   b. Not very attentive   c. Moderately attentive
        d. Quite attentive e. Extremely attentive

34B. Describe your level of attentiveness during online work for this course.
        a. Not at all attentive   b. Not very attentive   c. Moderately attentive
        d. Quite attentive e. Extremely attentive

35A. Describe your general frustration during face-to-face class.
        a. Not at all frustrated   b. Not very frustrated   c. Moderately frustrated
        d. Quite frustrated   e. Extremely frustrated

35B. Describe your general frustration during online work for this course.
        a. Not at all frustrated   b. Not very frustrated   c. Moderately frustrated
        d. Quite frustrated   e. Extremely frustrated

36A. Describe your level of happiness during face-to-face class.
    a. Not at all happy   b. Not very happy   c. Moderately happy
    d. Quite happy   e. Extremely happy

36B. Describe your level of happiness during online work for this course.
    a. Not at all happy   b. Not very happy   c. Moderately happy
    d. Quite happy   e. Extremely happy

37A. Describe your level of absorption/deep concentration during face-to-face class.
    a. Not at all absorbed   b. Not very absorbed   c. Moderately absorbed
    d. Quite absorbed   e. Extremely absorbed

37B. Describe your level of absorption/deep concentration during online work for this course.
    a. Not at all absorbed   b. Not very absorbed   c. Moderately absorbed
    d. Quite absorbed   e. Extremely absorbed

38A. Describe your general boredom during face-to-face class.
    a. Not at all bored   b. Not very bored   c. Moderately bored
    d. Quite bored   e. Extremely bored

38B. Describe your general boredom during online work for this course.
    a. Not at all bored   b. Not very bored   c. Moderately bored
    d. Quite bored   e. Extremely bored

39A. Describe your level of curiosity during face-to-face class.
    a. Not at all curious   b. Not very curious   c. Moderately curious
    d. Quite curious   e. Extremely curious

39B. Describe your level of curiosity during online work for this course.
    a. Not at all curious   b. Not very curious   c. Moderately curious
    d. Quite curious   e. Extremely curious

40A. Describe your general anxiety during face-to-face class.
    a. Not at all anxious   b. Not very anxious   c. Moderately anxious
    d. Quite anxious   e. Extremely anxious

40B. Describe your general anxiety during online work for this course.
    a. Not at all anxious   b. Not very anxious   c. Moderately anxious
    d. Quite anxious   e. Extremely anxious

41A. Describe your level of interest during face-to-face class.
    a. Not at all interested   b. Not very interested   c. Moderately interested
    d. Quite interested   e. Extremely interested

41B. Describe your level of interest during online work for this course.
      a. Not at all interested   b. Not very interested   c. Moderately interested
      d. Quite interested   e. Extremely interested

42A. Describe your general confusion during face-to-face class.
      a. Not at all confused   b. Not very confused   c. Moderately confused
      d. Quite confused   e. Extremely confused
42B. Describe your general confusion during online work for this course.
      a. Not at all confused   b. Not very confused   c. Moderately confused
      d. Quite confused   e. Extremely confused

43A. How often did you spend the expected amount of time in face-to-face class?
      a. Never b. Rarely   c. Sometimes   d. Often   e. All the time
43B. How often did you spend the expected amount of time completing online work for this course?
      a. Never b. Rarely   c. Sometimes   d. Often   e. All the time

*44A. How likely are you to apply the concepts and principles taught in this class to real problems or challenges in your life outside of class?
      a. Not at all likely   b. Not very likely   c. Moderately likely
      d. Quite likely   e. Extremely likely
* 44B. How personally meaningful was the content of this course?
      a. Not at all likely   b. Not very likely   c. Moderately likely
      d. Quite likely   e. Extremely likely

* Items excluded from Halverson and Graham's theoretical framework and not analyzed in this research.

DISSERTATION CONCLUSION

The purpose of this study was to propose, operationalize, and test a theoretical framework for learner engagement in blended learning environments. Despite widespread interest in learner engagement, a comprehensive framework for understanding engagement is elusive in general contexts and even less understood in those settings, which combine face-to-face and computer-mediated instruction. Current engagement models and instruments are inadequate due to contextual affordances (course and activity level vs. institutional) and to insufficient clarity about constructs and subconstructs of engagement. Clarifying definitions and constructs not only gives researchers a common language but provides guidance for future research in blended settings.

In Article 1, "Learner Engagement in Blended Learning Environments: A Conceptual Framework," we reviewed the existent literature on learner engagement. Finding a "duplication of concepts and lack of differentiation in definitions" (Fredricks, Blumenfeld, & Paris, 2004, p. 65), we expanded our review from the fields of educational psychology and human development, to also include disciplines with intersections with blended learning, such as artificial intelligence, human-computer interaction, and educational technology. Drawing upon this broadened base, we advanced several first order factors for cognitive and emotional engagement that might best encompass the affordances of blended context. We proposed that cognitive engagement is composed of *attention, effort and persistence, time on task, cognitive strategy use, absorption*, and *curiosity*. Emotional engagement, we suggested, is composed of positive energy indicators, including *interest and enjoyment, happiness*, and *confidence*, and negative energy indicators, including *boredom, frustration*, and *anxiety*. We advocated investigating the first order factor of *confusion* in greater detail, since depending upon the learner's feelings about the learning activity, confusion may indicate positive or negative energy (Baker, D'Mello, Rodrigo, &

Graesser, 2010; D'Mello, Lehman, Pekrun, & Graesser, 2014). We did not separate indicators by context in this model.

The purpose of Article 2, "Scale Development to Measure Learner Engagement in Blended Learning Environments," was to operationalize and test the proposed model of blended learning engagement using exploratory and confirmatory factor analysis. We developed and investigated the structural validity of a new end-of-course self-report instrument, which we called the Blended Learning Course Engagement Survey. The instrument accounted for context (online or face-to-face) and the cognitive and emotional aspects of learner engagement. Indicators measured their respective factors fairly well. However, results indicated that the original model be adjusted to separate factors by context, suggesting that face-to-face engagement indicators are not equivalent to online engagement indicators: flow perceived in a face-to-face context, for example, is somehow different from flow perceived in an online setting.

In addition, lack of discriminant validity between first order factors led to a respecification of the original models. We found it interesting that cognitive strategy use, conceived in various other frameworks as the core element of cognitive engagement, correlated highly with attention (.905) and effort and persistence (.994), both of which have been deemed behavioral engagement in alternative models (see also Henrie, Halverson, & Graham, 2015). This gives support to our assertion in Article 1 that these factors converge under cognitive engagement, "the expenditure and reception of mental energy" (Halverson & Graham, under review). Two comparable cognitive engagement models emerged. CE Model 3 was comprised of the factors of focused attention (specified by attention, effort and persistence, cognitive strategy use, and absorption) and curiosity; CE Model 4 was comprised of the factors of effort (specified by attention, effort and persistence, and cognitive strategy use) and flow (specified by absorption and curiosity).

First order factors in emotional engagement likewise converged under three constructs: positive emotional engagement (specified by enjoyment, happiness, and lack of detachment), negative emotional engagement (specified by anxiety, frustration, and confusion), and confidence. Since those indicators falling under positive emotional engagement are all *positive activating emotions* or their orthogonal opposites, *negative deactivating emotions,* and those specifying negative emotional engagement are classified as *negative activating emotions* (Feldman Barrett & Russell, 1998; Pekrun & Linnenbrink-Garcia, 2012), new questions arise as to the impact of energy-producing emotions (enjoyment, happiness, and attachment) and energy-depleting emotions (frustration, anxiety, and confusion) upon learner engagement.

Our revised theoretical framework for blended learning engagement is only the first step towards understanding how engagement is indicated in contexts that combine face-to-face and technology-mediated instruction. Further refinements to the engagement scale would produce even better measurements, especially in regards to the construct of flow. We utilized an end-of-course survey in this research, which attempted to measure course-level engagement (see Skinner & Pitzer, 2012, for further discussion of the levels at which student engagement has been studied). However, to measure engagement at the moment of the learning activity, further activity-level measures of engagement must be explored (Henrie, Larsen, Manwaring, Halverson, & Graham, under review; Sinatra, Heddy, & Lombardi, 2015; Wang, Bergin, & Bergin, 2014).

In conclusion, this dissertation has offered important insights to our understanding of blended learning engagement. We have found that context matters when learners report on their own engagement in settings that combine face-to-face and technology-mediated learning activities. We also found empirical support for our argument that the behavior and cognitive

engagement models can be combined into one and the underlying construct—cognitive

engagement—considered the root of behavioral manifestations of learner engagement.   These

findings can inform how we conceptualize and measure engagement in blended settings.

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