THE RELATIONSHIP BETWEEN INSTRUCTOR COURSE PARTICIPATION, STUDENT PARTICIPATION, AND STUDENT PERFORMANCE IN ONLINE COURSES

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A Dissertation Submitted to the Faculty of the University of
Tennessee at Chattanooga in Partial Fulfillment
of the Requirements of the Degree
of Doctor of Education: Learning and Leadership

The University of Tennessee at Chattanooga
Chattanooga, Tennessee

August 2020

ABSTRACT

Online learning has become ubiquitous with higher education and has catalyzed many changes in teaching and learning, particularly in academic technology. However, foundational frameworks for supporting learning in a virtual environment argue that learners need very similar, if not more, instructional engagement and support as the traditional classroom. Moore's (1989) three types of interaction and Garrison & Akyol's (2013) community of inquiry theoretical framework opine the importance of social engagement on the part of instructors and students in the online classroom, further asserting that learner-to-instructor interactions are essential to supporting student satisfaction and learning. Nevertheless, there are few studies, particularly quantitative studies, that examine the relationship between instructor participation in online courses and student participation and achievement. This study analyzed the relationship between select forms of instructor participation, including course announcements and discussion board posts, and student participation and achievement, represented by student course accesses, clicks within a course, time in a course, discussion board posts, and final course grade. The researcher utilized data available in the learning management system (LMS) log files from over 500 online master's degree courses delivered at a private nonprofit university in the Northwest United States. The results of the multiple regression and multivariate analysis of variance (MANOVA) analyses on the data from the logs showed significant relationships between instructor participation and student participation as well as student participation and achievement within an online course. No significant relationship was identified between instructor participation and student achievement. Potential explanations for this discrepancy and opportunities for future research are also discussed.

DEDICATION

I dedicate the growth and struggles represented within these pages to Otto Henry Thornbury. He was my motivation to power through as well as procrastinate endlessly. He is one of the reasons I finished, as well as the primary reason I considered walking away multiple times. He is my guiding light. While this work represents so much learned over the course of too many years, you, Otto, have taught me more in your time on this earth than all of my years. I am a better version of myself because of you, but I am here because of me.

Dr. Ted Miller is also a big part of my completing this final chapter of my doctoral journey. His unwavering belief in my intelligence and spirit, kept me believing that I could finish even when the finish line appeared to recede. Thank you for your kind and endless nagging, and for holding off your retirement until I finished.

ACKNOWLEDGEMENTS

I would like to recognize the guidance provided by my Dissertation Chair, Dr. Miller, who continuously helped keep this project focused and my writing as concise as possible. A great debt of gratitude is also owed to my Methodologist, Dr. Banks, for his support and expertise in analyzing the mounds of data collected. Finally, I would like to acknowledge the assistance, interest, and support of City University of Seattle Director of Information Technology, Kevin Brown, in the identification and extraction of data use in this study. This research study would not have been possible without the contributions of these key individuals and many others who continuously offered encouragement.

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LIST OF ABBREVIATIONS

EDM, Educational Data Mining

ID, Identification

IPEDS, Integrated Postsecondary Education Data System

IRB, Institutional Review Board

LMS, Learning Management System

MANOVA, Multivariate Analyses of Variance

MOOC, Massive Open Online Course

NCES, National Center for Education Statistics

PS, PeopleSoft

SIS, Student Information System

LIST OF SYMBOLS

b, The regression coefficient

β, Standardized regression coefficient

df, Degrees of freedom

F, F-ratio (test statistic used in ANOVA)

n, Sample size

η2, Eta-squared

p, Probability (p-value or significance of a test)

R, The multiple correlation coefficient

SE, Standard error

CHAPTER I

INTRODUCTION

Learning online is no longer an innovative approach to post-secondary education (Allen & Seaman, 2016). To the contrary, online education has become a cornerstone of higher education (Allen & Seaman, 2015). Integrated Postsecondary Education Data System (IPEDS) reported that over 70% of active degree granting institutions offered some form of distance learning in 2013 (Allen & Seaman, 2015). In 2016, over six million learners, just over 30% of all postsecondary enrollments, took at least one online course (Seaman, Allen, & Seaman, 2018). The number of students taking one or more online courses has steadily increased year after year, even when growth in overall enrollments in higher education is declining (Seaman et al., 2018).

Today's well-established modes of online education provide the flexibility and accessibility many adult learners need to pursue advanced education (Serhan, 2010). The Council of Regional Accrediting Commissions' (2011) standards for distance education and the competition inherent in this geographically borderless instructional modality have resulted in a plethora of best practices and guidelines for quality in online education. This literature on quality online instruction asserts that students have improved achievement of learning outcomes, satisfaction, and retention in online courses when high levels of interaction and community are present (Cobb, 2009; Garrison & Akyol, 2013; Kim, Kwon, & Cho, 2011; Shea, 2006). In fact, many of the best practices for face-to-face undergraduate education, outlined by Chickering and Gamson (1999), are supported by online learning researchers (Calsolaro Smulsky, 2012; Tirrell

& Quick, 2012; Wang, Doll, Deng, Park, & Yang, 2013), who assert that the same interaction techniques that support effective traditional classroom learning are also effective online. Early myths portraying online students working in isolation (Li & Akins, 2005) are simply not true in courses adhering to what the field has defined as best practice. The research shows that practices that facilitate interaction with peers and the instructor support student satisfaction and learning outcomes (Garrison & Akyol, 2013; Moore, Dickson-Deane, & Galyen, 2011).

As early as the 1980s, Moore (1989) argued the importance of interaction between students and other students, content, and instructors in distance education. At the beginning of the current century Garrison, Anderson, and Archer (2000) elaborated on Moore's constructs with the community of inquiry theoretical framework. The researchers argued that "a worthwhile educational experience is embedded within a community of inquiry that is composed of teachers and students – the key participants in the educational process" (Garrison et al., 2000, p. 88). In their model, the essential elements of a community of inquiry are social presence, cognitive presence, and teaching presence.

Of the three tenants of their framework, Anderson, Rourke, Garrison, and Archer (2001) asserted that teaching presence is the lynchpin for a successful community of inquiry. They argued that it is the instructor's presence within a course that initiates and supports cognitive and social presence. In their model, teaching presence includes a category for elements of course design and organization, facilitation of discourse, and direct instruction (Anderson et al., 2001). These categories were later re-conceptualized by Heuer and King (2004) as an instructor's role as planner, model, and coach, respectively.

The literature on teaching presence reflects the potential for a variety of impacts on the student experience. Shea (2006) found that the instructor's facilitation of discourse and effective instructional design, contributed to a student's sense of connectedness and learning in an online course. Ma, Han, Yang, and Cheng (2015) indicated a positive relationship between instructional design and organization as well as direct instruction and students' participation in an online course. However, few of these studies focused on the relationship between an instructor's participation (facilitation of discourse and direct instruction components of teaching presence as defined by Anderson et al. (2001)) and the students' reciprocal participation in an online course.

Hrastinski (2009) asserted that "participation [is] a condition for learning" (p. 78) and "learning occurs in interaction with others and… is an aspect of all human activity" (p. 79), a point supported by research on learning conducted by Bandura (1986), Jaldemark, Lindberg, and Olofsson (2005), and Vygotsky (1978). This may lead one to believe that participation online happens naturally. However, models such as the community of inquiry (Garrison & Akyol, 2013) indicate that student participation is cultivated by instructor efforts. In one study, if cultivated effectively, student participation was found to actually predict student success in online computer science courses (Romero, López, Luna, & Ventura, 2013).

Although traditional online courses are still focused on establishing community to foster student participation, continual advancements in technology, increased personal access to technology, and growth in a knowledge-based economy are pushing back on this traditional model (Johnson, Adams Becker, Estrada, & Freeman, 2015). New and emerging modes of online education, such as Massive Open Online Courses (MOOCs), competency-based education, and adaptive learning (Johnson et al., 2015) support elements of Moore's (1989) framework for interaction and Garrison and Akyol's (2013) community of inquiry theoretical framework, but in many instances instructor facilitated discourse and direct instruction are absent or modified (Paris, 2013; Tucker, Au, & Neely, 2015). Although existing models assert that interactivity as it is perceived through social, cognitive, and teaching presence is essential to effective online learning (Garrison & Akyol, 2013; Garrison et al., 2000; Garrison, Anderson, & Archer, 2010; Moore et al., 2011; Moore, 1989), new models appear to contradict existing literature on online learning (Paris, 2013). MOOCs, adaptive learning, and competency-based models emphasize student-to-content interaction and modify or remove the traditional instructor role (Johnson & Samora, 2016; Johnson et al., 2015). These conflicting models represent an opportunity for researchers to help inform teaching practice through the analysis of traditional forms of teaching presence and their relation to student participation and academic achievement.

Definition of Terms

The terms included in this section are referenced throughout this study. The definitions provided are taken from the literature on online education in most cases and are intended to operationalize concepts with varying of definitions for consistency within this study.

- Adaptive learning: Bryant (2016) defines adaptive learning as “data-driven, and in some cases, nonlinear approach to instruction and remediation, adjusting to each learner’s interactions and demonstrated performance level and subsequently anticipating what types of content and resources meet the learner’s needs at a specific point in time” (p. 3).
- Announcement: A course tool in the learning management system for communication from the instructor to students. The Blackboard announcement tool is used by instructors to post communications to students from within the course; these communications can also be emailed to course members (Blackboard Inc., 2016).
- Discussion board: WhatIs.com (May 2011) defines discussion board as a "general term for any online 'bulletin board' where you can leave and expect to see responses to messages you

have left" (para. 1). Messages left on a discussion board are referred to as posts. Discussion boards can also be read and do not require posting. In online courses discussion boards are used by instructors and students for asynchronous communication.

- Competency-based education: The Competency-based Education Network (2016) defines competency-based education as “an academic model in which the time it takes to demonstrate competencies varies and the expectations about learning are held constant” (para. 1). In addition, “Learners earn credentials by demonstrating mastery through multiple forms of assessment, often at a personalized pace” (Competency-based Education Network, 2016, para. 1). The university participating in this study uses the term performance-based education when referring to its competency-based courses.
- Educational data mining (EDM): The International Educational Data Mining Society (n.d.) defines data mining as the “[development of] methods for exploring the unique types of data that come from the educational setting, and using those methods to better understand student, and the settings which they learn in” (para. 1).
- eLearning: Koohang (2012) defines eLearning as “the delivery of education (all activities relevant to instructing, teaching, and learning) through various electronic media” (p. 68). Also referred to as online learning or distance learning.
- Integrated Postsecondary Education Data System (IPEDS): National Center for Education Statistics define IPEDS as:

> A system of interrelated surveys conducted annually by the U.S. Department of Education’s National Center for Education Statistics (NCES) … [to] gather information from every college, university, and technical and vocational institution that participates in the federal student financial aid programs. (para. 1)

- Learning analytics: Agudo-Peregrina, Iglesias-Pradas, Conde-González, and Hernández-García (2014) define learning analytics as the interpretation of learning data for the improvement of learning.
- Learning management system (LMS): Psaromiligkos, Orfanidou, Kytagias, and Zafiri (2011) state that LMSs "constitute the basic software platform for supporting web-based learning in an easy-to-use, pedagogically flexible and cost efficient manner, providing a uniform interface to [users], and promote portability of learning resources as well as interoperability between each other" (p. 188).
- Massive Open Online Course (MOOC): Allen and Seaman (2015) characterize a MOOC as a free, non-credit bearing, online course "designed for unlimited participation" (p. 8) made available to learners not registered with a particular institution.
- Microcredentials: Microcredentials Research Group (2016) define microcredentials as "a way of certifying that an individual has gained a specific skill or knowledge, or engaged in a particular experience … that extends to the social web in that the microcredential is represented in a digital format" (para. 2) that often contains the credential's criteria and evidence. Also referred to as digital or open badges, nanodegrees, or microdegrees.
- MySQL: The Oracle Corporation (2017) defines MySQL as an open source relational data management system.
- Participation: Hrastinski (2008) defines "online learner participation is a process of learning by taking part and maintaining relations with others. It is a complex process comprising doing, communicating, thinking, feeling and belonging, which occurs both online and offline" (p. 1761). For the purpose of this study, participation is defined as contributions to

the course in the form of announcements or discussion board posts as well as course activity (clicks) and time in the course as recorded by the learning management system.

- Performance-based education: See Competency-based education.
- Self-efficacy: Shea and Bidjerano (2010) define self-efficacy "as a subjective judgment of one's level of competence in executing certain behaviors or achieving certain outcomes in the future" (p. 1723).
- Social presence: Garrison and Akyol (2013) define social presence as "the ability of participants to identify with the group or course of study, communicate purposefully in a trusting environment, and develop personal and effective relationships progressively by way of projecting their individual personalities" (p. 107).
- Teaching presence: Anderson et al. (2001) define teaching presence as "the design, facilitation, and direction of cognitive and social processes for the realization of personally meaningful and educationally worthwhile learning outcomes" (p. 5).

Statement of the Problem

Despite assumptions about online learning that presented an opportunity to maximize faculty time (Berg, 2002; Rumble, 2004), research shows that demands of instructor time are not reduced when the physical classroom is removed. Spector (2005) argued that online courses are more demanding of instructor time. The literature on best practice in online instruction presents extensive examples of lengthy development and preparation of the online course space (Cavanaugh, 2005). When the course is finally ready for students, the instructor is expected to be an active participant in the resulting 24-hour learning environment (Jones & Johnson-Yale, 2005; Schulte, 2010).

More recent trends in online learning are changing the role of the instructor, often pushing more responsibility onto the learner and the technologies used to deliver course material. MOOCs, which have lost some of their original promise and fanfare (Johnson et al., 2015), rely primary on a student's intrinsic motivation and learner-learner and learner-content interactions within the course community (Hew & Cheung, 2014). Competency-based courses, which continue to gain popularity in higher education, also depend on a learner's self-motivation (Fain, 2015). Tucker et al. (2015) showed that in competency-based courses the role of instructor is often splintered into various roles, most commonly facilitator or mentor and grader or assessor.

MOOCs and competency-based courses have pushed the limits of existing instructional technology and catalyzed innovative technologies to meet the needs of new instructional modalities (Bryant, 2016; Harden, 2012; Johnson & Samora, 2016; Johnson et al., 2015; Kirp, 2013). Adaptive learning, which uses complex algorithms to track and place students on a learning path customized to their strengths and weaknesses, is a growing field (Johnson & Samora, 2016). Adaptive learning applications such as Flat World Inc. Boston, MA, Knewton Inc. NY, NY, and Pearson Inc. London, England, unbundle the faculty role and, in some cases, remove the traditional instructor role entirely from the course (Fain, 2014; Paris, 2013; Parry, Field, & Supiano, 2013). The technology of the adaptive learning environment assesses the learner's knowledge and presents content and activities in a personalized learning path that address gaps in the learners knowledge or skills and scaffold the learning experience to facilitate successful achievement of learning outcomes (Bryant, 2016; Johnson et al., 2015).

As institutions of higher education seek to reduce costs, while also increasing enrollments and fulfilling the unique expectations of today's learners, they push the boundaries of existing practice and explore new methodologies that may contrast with previous approaches. These new approaches may change the traditional instructor role in the course space (Paris, 2013; Tucker et al., 2015); relying more heavily on learner-learner or learner-to-technology/content interactions to support student success (Hew & Cheung, 2014; Johnson & Samora, 2016). It is therefore important to examine more traditional learner-instructor interactions supported in the existing literature. If instructor participation has little impact on student participation, perhaps institutions need not be concerned about online class size and maintaining the traditional faculty role online; universities might feel freer to explore alternative or even innovative approaches to supporting, facilitating, and assessing learning. However, if teaching presence is as essential to learning outcomes and satisfaction, as much of the existing literature argues (Agudo-Peregrina et al., 2014; Anderson et al., 2001; Garrison et al., 2000; Ladyshewsky, 2013; Moore, 1989; Sheridan & Kelly, 2010), higher education may unknowingly be pursuing a stance that will reduce learning and ultimately impact other components of the student experience, such as student-to-student interactions, which Agudo-Peregrina et al. (2014) argued needed instructor prompting.

Purpose of the Study

The existing literature related to online instruction fails to document the relationship between learner-instructor interaction (Moore, 1989), or teaching presence (Garrison et al., 2000), and student participation and achievement in online courses. This study focused on the direct instruction and facilitation of discourse components of teaching presence, which represent observable learner-to-instructor interactions and are referred to within this study as instructor participation. This study was designed to examine the relationship between instructor participation and student participation and achievement through the analysis of data related to the frequency of instructor announcements and discussion board participation, as well as student logins, time in the course, clicks within the course, discussion posts, and final grades. Instructor announcements and discussion board frequency serve as observable artifacts of direct instruction and facilitation of discourse. Student participation is then operationalized as frequency of logins, time in the course, clicks within the course, and discussion board posts. Student academic achievement is based on final course grade.

Research Questions

This study was guided by five research questions and hypotheses, which were designed to examine the relationship between instructors' course participation, measured by the posting of announcements and discussion board entries, and student's participation, measured by logins, time in the course, discussion board posts, and course content clicks, and academic achievement (measured by final grades) in an online course.

RQ1: Is there a relationship between the frequency of instructors' posting of announcements and student participation in an online course? Does the relationship vary by student age, gender, or number of credits completed?

$H_0$1: There is no relationship between the frequency of instructors' posting of announcements and student participation in an online course.

RQ2: Is there a relationship between the frequency of instructors' discussion board posts and student participation in an online course? Does the relationship vary by student age, gender, or number of credits completed?

$H_0$2: There is no relationship between the frequency of instructors' discussion board posts and student participation in an online course.

RQ3: Is there a relationship between the frequency of instructors' posting of announcements and student achievement in an online course? Does the relationship vary by student age, gender, or number of credits completed?

$H_0$3: There is no relationship between the frequency of instructors' posting of announcements and student achievement in an online course.

RQ4: Is there a relationship between the frequency of instructors' discussion board posts and student achievement in an online course? Does the relationship vary by student age, gender, or number of credits completed?

$H_0$4: There is no relationship between the frequency of instructors' discussion board posts and student achievement in an online course.

RQ5: Is there a relationship between student participation and achievement in an online course? Does the relationship vary by student age, gender, or number of credits completed?

$H_0$5: There is no relationship between student participation and achievement in an online course.

RQ6: Is there a difference in student participation in an online course based on the student's school affiliation or the course's affiliation with a particular school?

$H_0$6: There is no difference in student participation in an online course based their school affiliation and that of the course?

Rationale for the Study

Teaching online is demanding, particularly for new instructors who are often unfamiliar with online pedagogy (Batts, Pagliari, Mallett, & McFadden, 2010; Wolf, 2006). While research regarding best practices in online instruction abound, there are few prescriptive guidelines for instructors on how to successfully implement teacher presence in an online course (Mandernach, Gonzales, & Garrett, 2006).

The framework for a community of inquiry developed by Garrison et al. (2000) and the model of interaction outlined by Moore (1989), are widely accepted as frameworks for effective online instruction. Both models infer instructor participation in the course. Moore (1989) described learner-instructor interaction as a dialog between student and the instructor where the instructor presents content to which the student responds, prompting the instructor to provide additional "counsel, support, and encouragement" (Moore, 1989, p. 3) to each student as needed. Garrison et al. (2000) included facilitating discourse and direct instruction in their definition of teaching presence, which is a key component in the community of inquiry framework. However, the research is less definitive on the components of these two models that have the largest impact on student satisfaction and achievement. Dennen, Aubteen Darabi, and Smith (2007) found that student-to-instructor interaction was associated with higher student satisfaction. However, Sheridan and Kelly (2010) found that teaching presence component, course design and organization, were more important than direct instruction or the facilitation of discourse to students in an online course.

Although Hrastinski (2008) asserted that student participation is essential to learning, participation is facilitated by social presence within the learning community, which Garrison and Akyol (2013) argued hinges on effective teaching presence. Teaching presence, as defined by Garrison and Akyol (2013), has three components – course design and organization, facilitation of discourse, and direct instruction. Here again the importance of instructor participation in online courses is inferred, but no relationship between instructor participation and increased student participation has been established in the literature.

Potentially related to deficiency in the literature is the relative infancy of learning analytics in empirical research (Agudo-Peregrina et al., 2014; Johnson et al., 2015). Previous studies on teacher presence have utilized surveys, case studies, or small samples of courses for the evaluation of student participation. Yet few studies have utilized learning management system (LMS) activity data to analyze student participation (Agudo-Peregrina et al., 2014; Joksimović, Gašević, Loughin, Kovanović, & Hatala, 2015; Mohamad & Tasir, 2013); even fewer studies have looked at instructor participation (Ma et al., 2015). Collecting and relating these data has the potential to increase the field's understanding of the impact of instructor participation in online courses. Furthermore, the methods used to collect and analyze direct data on instructor and student participation in online courses will contribute to the development of actionable learning analytics to inform policy, practice, and innovation.

Theoretical/Conceptual Framework

The importance of social interaction to learning outcomes is evident in several foundational learning theories. The constructivist learning theories proposed by Vygotsky (1978) emphasized the social nature of learning, arguing that learner interaction and verbalization solidify learning. Vygotsky (1978) asserted that all learning is social in the sense that it applies and/or is informed by the tools and ideas acquired through interactions. Vygotsky's theory is supported by Bandura's (1986) social cognitive learning theory, which emphasized that learning takes place through the observation of others. Bandura (1986) argued that observations can result in a kind of knowing through the mind's eye that does not require demonstration. More recently Bandura (2006) contended that the growth and accessibility of digital media increases the role of observational learning or learning through the experience of others. Such early foundational theories directly support instructional practices that facilitate peer-to-peer and peer-to-instructor interaction and collaboration.

Despite considerable difference in delivery from traditional instructional modalities, many researchers advocate for social interaction in online instruction (Chickering & Gamson, 1999; Garrison & Akyol, 2013; Moore, 1989). In 1989, Moore proposed a three-part interaction framework, which argued that effective online instruction incorporates many, if not all, of three interaction types: learner-content interaction, learner-instructor interaction, and learner-learner interaction. Moore's (1989) framework, originally proposed as an editorial in *The American Journal of Distance Education,* became the basis for a wealth of future research on interaction in online courses. Research has supported, to varying degrees, the importance of the three types of interaction to the satisfaction and perceived learning of online students (Kuo, Walker, Schroder, & Belland, 2014; Swan, 2001).

Moore's (1989) interaction framework fits neatly into the community of inquiry theoretical framework developed by Garrison et al. (2000), which argued that "learning occurs within the community through the interaction of three core elements … cognitive presence, social presence, and teaching presence" (p. 88). These authors defined cognitive presence as the ability of learners to construct meaning from course communication. Cognitive presence aligns to all three of Moore's interactions as learners construct meaning from content, peers, and their instructor. Learner-learner and learner-instructor interactions are informed by social presence, which is the capacity of participants to represent themselves in the digital environment, build relationships, identify with the community, and communicate effectively (Garrison & Akyol, 2013). Finally, teaching presence, defined as course design and organization, facilitation of discourse, and direct instruction, (Anderson et al., 2001) provides a framework for Moore's learner-instructor interaction, while also supporting learner-learner and learner-content interaction. Figure 1 shows how the components of Moore’s (1989) interaction framework align with Garrison and Akyol’s (2013) community of inquiry theoretical framework and where the constructs overlap.

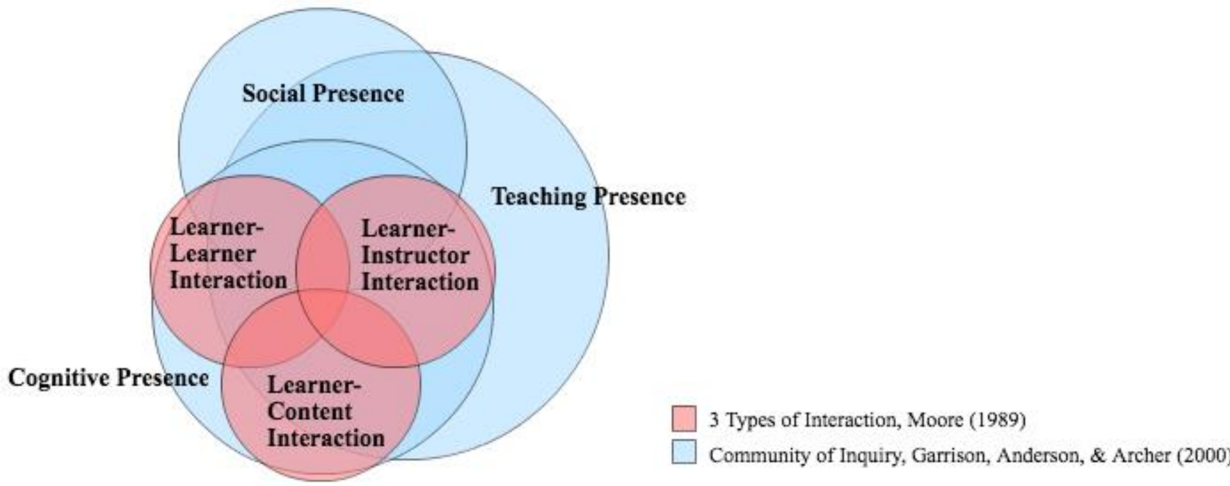

Figure 1 Relationship between the foundational theories of this study’s conceptual framework

Anderson et al. (2001) argued that teaching presence is the cornerstone of a successful community of inquiry. Without the effective development of teaching presence through thoughtful and supportive course design, continuous scaffolding of meaningful discourse, and relevant and necessary direct instruction, social and cognitive presence flounders. Cognitive presence, the basis of learning in Garrison and Akyol’s (2013) model, is supported by social presence, which facilitates exposure to new ideas, differing perspectives, and inaccurate assumptions. Teaching presence is responsible for providing the opportunity for cognitive and social presence.

Implied within the Moore (1989) and Garrison and Akyol's (2013) models is the importance of student participation in the learning process. Participation through contributions to communication in the course makes cognitive presence visible (Agudo-Peregrina et al., 2014). The instructor who creates opportunities for interaction through effective teaching presence is also creating opportunities for student participation in the learning process. Such practices are supported by social cognitive and constructivist learning theories. The theories assert that individuals learn by observing and modelling, through language and other shared cultural objects, and by establishing connections to existing knowledge (Schunk, 2012; Vygotsky, 1986). Aligned with the argument by Vygotsky (1978) that individuals learn through social interactions, Hrastinski (2009) argued that online learner participation is synonymous with learning. Hrastinski (2009) opined that to improve online learning, learner participation must be maximized.

Following this line of inquiry, this research study was designed to examine how the quantity of instructor participation, characterized by teaching presence, direct instruction, and the facilitation of discourse (Garrison & Akyol, 2013), relates to student participation within an online course. Furthermore, the study was designed to determine if higher student participation correlates to higher academic achievement, as suggested by Hrastinski (2009). Figure 2 shows how this study conceptualizes the relationship between the components of Garrison et al.'s (2000) community of inquiry and Moore's (1989) types of interactions utilized in this study – including, participation of instructor and student, and student academic achievement.

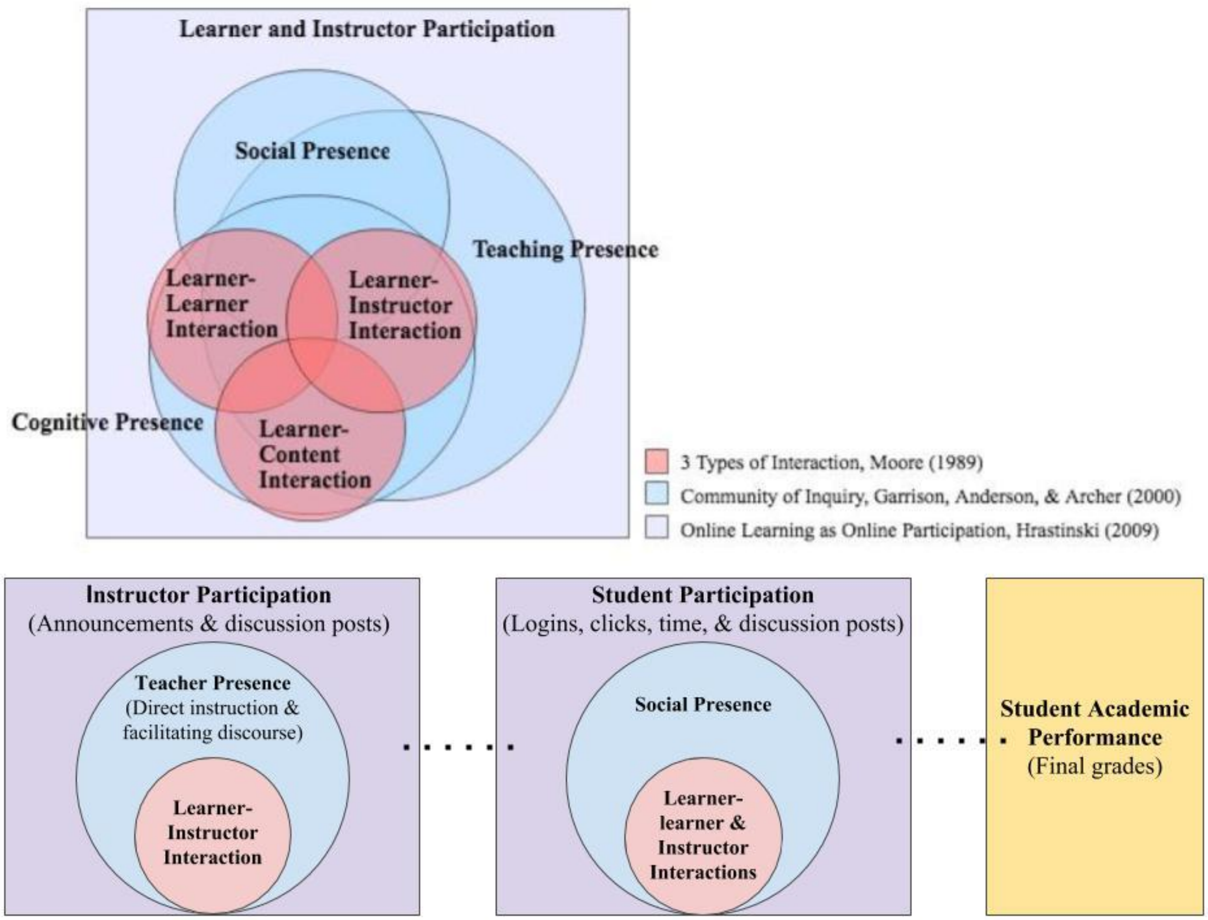

Figure 2 Conceptual framework representing the relationship between the community of inquiry theoretical framework, Moore's (1989) interaction framework, and Hrastinski (2009) theory of learning as online participation

Significance/Importance of the Study

The literature indicates that student participation is generally considered an essential component to learning outcomes and student satisfaction with online courses (Hrastinski, 2008, 2009). Research on online community and social presence suggests that teacher presence is the foundation of a successful learning community (Anderson et al., 2001). Moreover, studies have correlated teacher presence with student perceived learning and overall satisfaction with online courses (Moore, 1989; Sheridan & Kelly, 2010).

Facilitating an online course demands considerable instructor time when research supported presence and interaction strategies are utilized (Cavanaugh, 2005; Spector, 2005). Institutional efforts to increase online course size to improve financial returns will further strain demands on instructor time. Constraints on instructor time could be alleviated if alternative course facilitation strategies, less dependent on instructor participation, are employed. Furthermore, if instructor participation has little impact on student participation and achievement in online courses, alternative facilitation strategies might be expanded. For example, future research might focus on methods that maintain student satisfaction and achievement through effective use of technology that supports learner-content and learner-learner interactions. However, should instructor participation correlate to increased student participation and achievement, institutional policy and instructional practices that support high learner-instructor interaction and teaching presence should be supported (Anderson et al., 2001; Chickering & Gamson, 1999; Moore, 1989).

To date, much of the literature on teaching presence in online courses has utilized survey instruments for self-reports from students and faculty on their perceived participation and/or learning as well as their satisfaction with the experience. Self-reported data is susceptible to a variety of influences that affect the validity of findings (Gliner, Morgan, & Leech, 2009; Kahneman, 2011). To address these challenges this research study utilized objective data taken from the LMS database to directly represent student course participation as it relates to instructor participation in a course. Data from the LMS open database has rarely been used to analyze instructor activity (Ma et al., 2015). This study demonstrates just some of the research opportunities represented un the vast LMS data, which could be harnessed to inform practice and policy.

Methodological Assumptions

Utilizing the Blackboard open database to ascertain user actions within online courses is a relatively new proposition for institutions of higher education (Ma et al., 2015). It was necessary for the researcher to assume that the data within the LMS open database are an accurate and reliable representation of user participation. The participating institution in this study required the use of the Blackboard LMS in all online courses offered in the United States. The researcher assumed that all courses in the study used Blackboard as the institution required. For example, the researcher had to assume that instructors were not using synchronous tools, such as video conferencing, in place of the asynchronous discussion boards required by the institution. Furthermore, weekly instructor announcements and discussion board participation were required for online courses at the participating institution (City University of Seattle, 2013).

The community of inquiry has three main components. This study focused on just one component, teaching presence, and two of the three categories within teaching presence: direct instruction and the facilitation of discourse. The researcher included observable and LMS data logged interactions by the instructor within online courses and, therefore, assumed that the individual components of the community of inquiry theoretical framework (Garrison & Akyol, 2013), specifically teaching presence, could be analyzed in isolation from the model's other components. This assumption was supported by the model's authors who developed a tool that would assess teaching presence as a component of a community of inquiry (Anderson et al., 2001). Furthermore, Shea, Pickett, and Pelz (2003), Nagel and Kotzé (2010), and Ma et al. (2015) also looked expressly at teaching presence without full consideration of the community of inquiries' other components of social presence and cognitive presence.

The researcher included qualifiable and LMS logged learner-learner and learner-content interactions in the analysis. Making the assumption is that these interactions were the result of instructor-to-learner interaction (Moore, 1989) The analyses compared overall instructor participation online, with aggregates of student participation and achievement in online courses. In one of the few studies examining instructor participation directly, Beer, Clark, and Jones (2010) looked at student activity relative to instructor discussion board posts in online courses. The researchers concluded student activity increased when instructors were active participants in discussion boards.

Delimitations of the Study

This study utilized data from graduate level online courses from a small, not-for-profit university in Seattle, Washington. The study is limited to 10-week online courses at the master's level that were taught within the United States in an asynchronous format. These course parameters were chosen because these courses were designed and taught in a relatively consistent format. The courses typically used announcements for general course communications to the class and discussions almost exclusively for weekly course interactions.

The data for this study were extracted from Blackboard's open database for the four most recent terms at the institution (one calendar year), which included approximately 550 courses. Methodologies to identify and extract data described in this study may not be directly applicable to other LMSs as they may have differing data structures, instructional tools, and course designs. Furthermore, participation in this study is defined as a measure of user logins, time in the course, clicks within a course, and contributions via the discussion board or announcements. LMSs typically provide a variety of tools that support participation activities, such as blogs, wikis, and virtual classrooms. These LMS tools were excluded from data mining queries because they were used so infrequently in courses at the participating institution. However, each LMS tool has the potential for future research, such as their implications for learner-instructor interactions, direct instruction, and student participation.

Limitations of the Study

Participation in this study was a measure of user logins, clicks with the course, time in the course, and contributions via the discussion board or announcements. The study was designed to help the researcher understand any relationships between instructor participation in online courses and student participation and academic performance represented by final course grades. While the use of final grades to represent learning is controversial (Allen, 2005; Berrett, 2012; Brookhart et al., 2016), many researchers continue to use final grades as a measure of academic performance similar to this study, as is evident in a recent literature review of educational data mining by Papamitsiou and Economides (2014). Furthermore, the study was not intended to evaluate the quality of instructor or student participation, merely the frequency. The study did not control for differentiation in student participation based on their interest or the importance of the class to their course of study. This may be a considerable limitation as Joksimović et al. (2015) found that student differences in participation correlated to whether a course was an elective or required. Future research might seek to establish parameters for the measurement of participation quality, such as length of post, citations, or the introduction of new ideas as well as student interest in course material.

The study does not account for activities occurring outside the LMS or with tools that are beyond the scope of the study’s data mining parameters. Student and instructor interaction via email, chat, phone, blogs, etc. are purposely not accounted for. However, the sample is sufficiently large that anomalies of use, such as courses without discussion boards, were removed without great consequence. Future researchers might choose to incorporate more diverse types of interaction for a richer depiction of online participation.

Finally, study results do not verify that instructor participation has a direct cause and effect on student participation (Gliner et al., 2009). Results are not directly generalizable beyond the institution used in the study due to the research methodology and the population's specific online course guidelines and facilitation requirements. Nonetheless, this researcher's findings contribute to the literature on student participation, teaching presence, and LMS data analytics. Future researchers should consider an experimental approach with random sample that includes a greater diversity of higher education institutions to build on the results of the following research.

CHAPTER II

LITERATURE REVIEW

Online learning developed and continues to grow in popularity out of a need to make learning more accessible to individuals in various phases of life and with varying personal situations, but with a desire to continue their professional and academic development (Fedynich, 2014). The National Center for Education Statistics reported that adult learners (ages 25+) made up over half the part-time undergraduate enrollments at 4-year institutions in 2016. The traditional classroom is often unappealing or not an option for the adult learner population due to access limitations or obligations such as employment and family (Fedynich, 2014). The growth in the adult learner population has contributed to the ubiquity of online instruction at institutions of higher education (Allen & Seaman, 2016). Allen and Seaman (2015) reported that 70.7% of degree granting institutions offered online classes and that over six million students took at least one online course in 2016 (Seaman et al., 2018). Furthermore, online enrollments continued to grow in 2016 despite the overall decline in enrollment in higher education in the US (Seaman et al., 2018).

As the popularity and acceptance of online learning continues to grow, institutions of higher education are looking for ways to meet the changing needs and expectations of today's learners (Johnson et al., 2015). Competition among colleges and universities for students, reduced state funding, and the need to do more with less are fueling additional changes and innovations in post-secondary institutions (Macfadyen & Dawson, 2010). New trends in higher education, such as competency-based education, microcredentialing, and adaptive learning, are pushing the boundaries of established online learning methodologies and best practice (Bryant, 2016; Johnson et al., 2015). Where online learning introduced a new delivery methodology, these new trends focus more on the process of instruction and often decouple the instructor from the learning experience (Johnson & Samora, 2016; Tucker et al., 2015). This challenges over a quarter century of research on effective online instruction that emphasizes the importance of teaching presence and interaction, particularly interaction between the student and instructor, in the online classroom (Chickering & Gamson, 1999; Garrison & Akyol, 2013; Garrison & Cleveland-Innes, 2005; Ladyshewsky, 2013; Moore, 1989).

Learning analytics, particularly the data collected by learning management systems, extends opportunities to better understand the conditions and behaviors that support learning in the online environment (Baker & Siemans, 2014; Gašević, Dawson, Rogers, & Gasevic, 2016; Siemans & Gašević, 2012). LMS log files capture user activity and outcomes within the online learning environment, providing detailed quantitative accounts of individual learning experiences (Baker & Siemans, 2014; Siemans & Gašević, 2012). New research utilizing LMS and student information system (SIS) data, has already contributed new knowledge to the field, some of which draws into question established principles, such as the value of learner-learner interaction (Hernández-García, González-González, Jiménez-Zarco, & Chaparro-Peláez, 2015; Kim, Park, Yoon, & Jo, 2016). Just as the LMS captures data on student activity, it also records the actions of instructors in the course. Instructor activity data may provide additional insights into the relationship between instructor participation and student participation and achievement. For example, Beer et al. (2010) found that increased instructor participation in online discussion forums had a positive relationship to student activity within a course.

This chapter includes a review of two foundational frameworks for online learning; (1) three types of interaction developed by Moore (1989), and (2) the community of inquiry theoretical framework established by Garrison and Akyol (2013). Greater attention will be given to the instructor-learner interaction and teaching presence components of these frameworks as they relate to instructor participation in the learning environment. The current literature on participation in the online classroom will also be reviewed. The chapter will close with an exploration of the current use of LMS data by researchers to answer questions related to the learning experience – more specifically the instructor's impact on learning in the virtual environment.

Teaching and Learning Online

Online instruction developed out of the availability of new technologies that could support remote access and communication and the need to educate a new kind of workforce – a knowledge-based workforce (Bates, 2015). The format and methods of the early online classroom would mimic those of the traditional face-to-face classroom; some even requiring synchronous meetings (Pittman, 2013). In starting the experimental high school, Benton Harbor, the University of Nebraska indicated that their goal was to work within their existing instructional resources to provide training that met their standards of quality for graduation (Moore & Kearsley, 2011). Although the basic instructional premises are the same, the realities of the technology being used to deliver instruction at a distance necessitated new theories and frameworks for teaching and learning (Moore, 1989).

The foundational theories of learning have informed and revised online learning practices, just as they did in the traditional classroom. Social and constructivist instructional methodologies that support active learning and student interactions with peers, instructors, content, and systems are recognized as essential to student satisfaction and learning online (Bell & Federman, 2013; Chickering & Gamson, 1999; Garrison & Akyol, 2013; Kuo et al., 2014; Ladyshewsky, 2013; Macfadyen & Dawson, 2010; Moore, 1989). In fact, the 2001 Council of Regional Accrediting Commission's guidelines for online courses, asserted that online course work should be more interactive than traditional courses out of concerns related to academic integrity (Battalio, 2007). While the reasoning behind the guidelines is varied, this particular outcome supports Moore's (1989) theory of transactional distance, which asserted the importance of context and individual perspective to learning. Anderson et al. (2001) asserted a few years later that social interaction is essential to learning, stating that, "cognition cannot be separated from the social context" (p. 92).

Aligned with the research of Moore (1989) and Anderson et al. (2001), other research on best practice in online learning began to coalesce around the foundational research of Dewey (1959), which asserted that learning is fundamentally a social process that is supported by opportunities to interact and collaborate with a community of learners (Anderson et al., 2001; Battalio, 2007). Researchers stressed that a community of learners provides opportunities for students to confront new and conflicting ideas, which creates cognitive dissonance within the learner and the opportunity to resolve internal conflicts and establish new thought patterns (Anderson et al., 2001). These interactions support learner cognition, which facilitates learning (He, 2013; Picciano, 2002; Vygotsky, 1986). For these reasons foundational theories and models within online learning, including the three types of interaction framework developed by Moore (1989) and the community of inquiry theoretical framework by Garrison and Akyol (2013), are founded on social and constructivist learning methodologies. This study draws on the social constructivist principles presented in these two frameworks and add to the literature on the instructor's relationship to student participation and achievement in online courses.

Three Types of Interaction

As one of the first researchers to focus on interaction in courses taught at a distance, Moore developed the theory of transactional distance for distance education (Garrison & Cleveland-Innes, 2005; Moore, 1993). The term "transactional" stems from Dewey's (1938) theory of knowledge as transaction, which asserted that knowledge is influenced by the environment as well as an individual's perceptions of the experience (Giossos, Koutsouba, Lionarakis, & Skavantzos, 2009). Moore (1993) defined transactional distance as a "pedagogical concept" (p. 22) pertaining to the altered relationships between instructor and learner when separated by space and time in a distance learning setting. The original transactional distance education theory had three variables: dialog, structure, and learner autonomy (Moore, 1993). Moore suggests that the terms dialog and interaction are synonymous. Later he further delineated interaction into three types: learner-instructor, learner-content, and learner-learner (Garrison & Cleveland-Innes, 2005; Moore, 1989). Moore's (1989) types of interaction spurred much research into interaction in distance education (Battalio, 2007; Garrison & Cleveland-Innes, 2005; Kuo, Walker, Belland, & Schroder, 2013; Macfadyen & Dawson, 2010).

Moore (1989) argued that instructors should design courses that provide multiple opportunities for each type of interaction in order to support learning and student satisfaction with the learning experience. Each interaction by the learner – with the instructor, other learners, or the content – is a transaction that either increases or reduces distance in the learning experience. Moore (1993) opines that interactions facilitated by the course structure should be designed with the learning outcomes and the diversity of the learners' perspectives and needs in mind.

Researchers using LMS log files found differing relationships between the three types of interaction and student performance. Joksimović et al. (2015) and You (2016) found learner-content interaction to be the most significant predictor of student performance in online courses. Furthermore, Joksimović et al. (2015) found a negative relationship between learner-instructor interactions and achievement. The researcher suggested that these finding may reflect the characteristics of the student that seeks or requires help from the instructor rather than the impact of instructor interactions with students (Joksimović et al., 2015). Such findings could also reflect differences in course design and organization, which are more difficult to account for (Gašević et al., 2016). Of the research identified, only Macfadyen and Dawson (2010) argued the importance of learner-learner interaction to students' academic achievement. Their researched showed the number of discussion board posts made by students to be the most significant predictor of learner performance (Macfadyen & Dawson, 2010).

Similar findings were found by researchers exploring Moore's types of interaction and student satisfaction. The findings of Kuo et al. (2013) supported the importance of all three interaction types. Kuo et al. (2013) found that all three of Moore's interaction variables were correlated to and could predict student satisfaction. However, their findings indicated that learner-content and learner-instructor interactions had significantly greater influence on learner satisfaction than did learner-learner interaction. This effect was somewhat mediated by whether the student was enrolled in undergraduate or graduate coursework. Graduate students placed a greater emphasis on learner-learner interaction, but still less than the other two interaction types (Kuo et al., 2013). Battalio's (2007) research also supported the importance of learner-instructor interaction upon student satisfaction, but more recent research by Kuo et al. (2014) argued that learner-instructor interaction has only a weak correlation to student satisfaction, and learner-learner interaction has no significant correlation. According to the research of Kuo et al. (2014), the only interaction type with a significant impact on learner satisfaction was learner-content.

As Moore (1989), Battalio (2007), and Bell and Federman (2013) asserted, the interactions required of learners should match the course's learning objectives as well as student needs. You (2016), for example, indicated that the courses included in his sample were designed for individual learning with very few opportunities or requirements for interaction. Conversely, Macfadyen and Dawson (2010) included courses with a discussion board requirement and went on to assert that regression models would need to align with the instructor's intention and the design of the course. Finally, Joksimović et al. (2015) opined that the type of course, be it foundational, elective, or core, also impacted the amount of interaction observed. The authors hypothesized that the differences were related to the learner's experience in online courses, importance of the course to program of study, and interest in the topic (Joksimović et al., 2015).

These findings highlight a need for more research into the impact of Moore's (1989) three types of interaction and student achievement. In 1993, Moore asserted that learned-learner and learner-content interactions are facilitated by learner-instructor interaction. He stated that content interaction "is a form of learner-instructor dialogue because the learner has an internal or silent interaction with the person who... organized a set of ideas of information for transmission" (Moore, 1993, p. 25).

Moore (1989) argued that the lack of individualized interaction between student and instructor in courses designed for learner-content interaction requires the student to be internally motivated and monitor their own learning. Furthermore, generalized content built into a course is often at odds with constructivist theories, which draw on the unique experience of the learner (Moore, 1989; Vygotsky, 1978). Moore (1989) asserted, “each student’s response to the presentation is different, and so the response to each student [by the instructor] is different” (p. 3). Many researchers have echoed Moore’s (1989) sentiment that learner-instructor interaction is essential to learning (Battalio, 2007; Dennen et al., 2007; Ma et al., 2015). The teaching presence construct, part of the community of inquiry theoretical framework developed by Garrison et al. (2000), for example, provides additional support for the importance of the instructor to facilitating student participation and the overall effectiveness of online learning.

Community of Inquiry

Garrison et al. (2000) elaborated on Moore’s transactional distance theory to incorporate what they termed, educational presence. They argued that educational presence “is more than social community and more than the magnitude of interaction among participants” (Garrison & Cleveland-Innes, 2005, p. 134). Garrison et al. (2000) argued that an effective educational experience is “embedded in a community of inquiry” (p. 88) regardless of the mode of delivery, although it calls for special considerations in distance learning. The community of inquiry theoretical framework has three elements: cognitive presence, social presence, and teaching presence (Garrison & Akyol, 2013). These three elements are further delineated into categories for research purposes. Cognitive presence consists of triggering events, exploration, and integration (Garrison & Akyol, 2013). Social presence includes emotional expression, open communication, and group cohesion (Garrison & Akyol, 2013). Lastly, examples of teaching presence are categorized as course design and organization, facilitation of discourse, or direct instruction (Anderson et al., 2001). The community of inquiry theoretical framework aligns with collaborative constructivist approaches to learning by encouraging knowledge construction through communication and interaction with others in activities that define each category (Dewey, 1959; Garrison et al., 2000).

Researchers in online learning have studied the community of inquiry as a whole as well as focused on its individual elements, and have reported correlations to student satisfaction and perceived learning (Akyol & Garrison, 2008; Cobb, 2009; Enightoola, Fraser, & Brunton, 2014; Shea & Bidjerano, 2009; Sheridan & Kelly, 2010; Swan et al., 2008). Akyol and Garrison (2008) found a significant relationship between all three elements of the community of inquiry theoretical framework and student satisfaction. Additionally, in their study researchers found a significant relationship between teaching presence, cognitive presence, and perceived learning. Studies by Cobb (2009) and Joo, Lim, and Kim (2011) used the Social Presence Scale and the Satisfaction Scale (Gunawardena & Zittle, 1997) to measure social presence. Both studies found significant positive correlations between social presence and student satisfaction. Beyond student satisfaction with the learning experience, Anderson et al. (2001) argued "high levels of social presence with accompanying high degrees of commitment and participation are necessary for the development of higher-order thinking skills and collaborative work" (p. 94).

Similar to the importance of learner-instructor interaction in Moore's (1989) framework, Garrison et al. (2000) assert that teaching presence is the central pillar of a community of inquiry. Teaching presence creates opportunities for the social and cognitive presence necessary for an effective community of inquiry and supports their continuous development throughout the course (Garrison et al., 2000). Consistent with learner-instructor interaction, teaching presence is how the instructor connects with and supports students through course content or direct engagement (Anderson et al., 2001). The instructor's presence and interactions with learners are essential to the community of inquiry theoretical framework.

Teaching Presence

Anderson et al. (2001) defined teaching presence as "the design, facilitation, and direction of cognitive and social processes for the purpose of realizing personally meaningful and educationally worthwhile outcomes" (p. 5). Specifically, teaching presence is the selection and organization of course content, presentation of course content, "intellectual and scholarly leadership" (Anderson et al., 2001, p. 8), subject matter expertise, directing knowledge, directing attention, confirming understanding, diagnosing misconceptions, and "encouraging active discourse and knowledge construction" (Garrison et al., 2000, p. 93). Cognitive presence and the social presence that supports it, are dependent on teaching presence (Garrison & Akyol, 2013; Shea & Bidjerano, 2009).

Teaching presence and learner-instructor interaction, as defined by Garrison and Akyol (2013) and Moore (1989) respectively, require active participation by the instructor in a way that encourages student participation by modeling desired behavior, managing the group interactions, and supporting the unique and diverse needs of each student (Anderson et al., 2001; Sheridan & Kelly, 2010). Anderson et al. (2001) defined the three categories of teaching presence as course design and organization, direct instruction, and facilitation of discourse. The last two categories of teaching presence, direct instruction and facilitating discourse (Anderson et al., 2001), are central to this study as they align with Moore's (1989) learner-instructor interaction construct and also represent observable examples of instructor participation in an online course (Hrastinski, 2009). Furthermore, the study location and the course included in this study provide a relatively high degree of consistency in course design and organization due to institutional policy and requirements pertaining to course how courses are conducted.

Although Anderson et al. (2001) asserted that of the three tenets of the community of inquiry theoretical framework teaching presence is the component that instructors have the most control over, other researchers have argued that it is also the most expensive and least scalable component (Agudo-Peregrina et al., 2014; Joksimović et al., 2015). Unlike cognitive presence and social presence, which can be designed into a course content, tools, and expectations of learners; learner-instructor interactions, such as direct instruction and facilitation of discourse, require the instructor to provide for the unique needs of the class and individual students. Many of these activities still require human intervention, which is inherently limited and potentially costly. Nonetheless, various studies have supported the importance of teacher presence to student satisfaction and learning (Agudo-Peregrina et al., 2014; Ma et al., 2015; Sheridan & Kelly, 2010). Sheridan and Kelly (2010) for example, found that the most important aspects of teaching presence to students were those related to communicating course expectations as well as instructor responsiveness to students. The authors asserted that their findings support greater emphasis on effective instructor communication (Sheridan & Kelly, 2010). However, Ma et al. (2015) found that instructor design and organization strategies had a greater impact on students' activity than direct instruction. Notwithstanding, the researchers also argued that instructor feedback to students is also statistically correlated to student completion of learning tasks.

Research on the importance and impact of teaching presence is still divided. Campbell (2014) asserted that the findings of past research using survey instruments, which have reported correlations between teacher presence and student achievement, do not hold up under experimental manipulations. The experimental approach utilized by Campbell (2014) showed no correlation between teaching presence and student discussion board activity or achievement. However, it should be noted that Campbell's (2014) independent variable was limited to personalized email from the instructor. It is possible that other types of instructor participation, such as discussion board participation and announcements, as is included in this study, may have different results. For example, Kim et al. (2016) and King and Tanner (2015) found that discussion board activity and the quality of discussion board posts were increased when instructors were active participants in the discussions. Campbell's (2014) opposing results support the need for more research on the effects of teaching presence on student participation and performance online.

Participation as Visible Evidence of Interaction, Teaching Presence, and Learning

The concepts of participation, interaction, and engagement often overlap and are operationalized in a variety of ways in the literature (Beer et al., 2010; Henrie, Halverson, & Graham, 2015; Hrastinski, 2008, 2009; Morris, Finnegan, & Wu, 2005; Ravenna, Foster, & Bishop, 2012). Morris et al. (2005) defined participation as "student engagement in specific learning activities" (p. 224) including page views, discussion posts read, and original discussion postings. Henrie et al. (2015) operationalized engagement as frequency of logins, number of postings, responses and hits, frequency of posts or views, participation, and time spent online or a combination therein (p. 43), where participation is an observable indicator of engagement. Additionally, Wise, Speer, Marbouti, and Hsiao (2013) argued that online learner listening behaviors, such as reading the posts of others, are an important component of student participation online. Distinct activities by the learner, which are recorded in LMS activity logs, have been used as proxy for participation by many researchers (Kim et al., 2016). Beer et al.

(2010), for example, asserted that clicks can be used as a proxy for participation in an attempt to capture the active types of participation described by Morris et al. (2005) and Henrie et al. (2015), as well as the more passive types of participation described by Wise et al. (2013).

These descriptions of engagement are supported by Hrastinski (2009), who proposed a theory of online learning as participation in online courses. Hrastinski (2008) argues that participation is a “complex process comprising doing, communicating, thinking, feeling, and belonging, which occurs both online and offline” (p. 1761). The researcher argued that the measurement of online participation should go beyond the frequency of student activity to include more internal impacts to a learner. However, much of the existing research looks at quantitative measures such as logins, clicks, and posts with fewer studies looking at the less quantifiable elements, such as thinking and feeling, included in Hrastinski’s (2008) comprehensive definition of participation. This study uses the term participation to represent measurable student participation in an online course and the observable (by the student) participation of the instructor; analyzing quantitative data related to participation by learners and instructors.

Learner participation, in the various ways it has been defined in the literature, is positively correlated with perceived satisfaction (Henrie et al., 2015; Hrastinski, 2008) and performance (Beer et al., 2010; Calafiore & Damianov, 2011; He, 2013; Henrie et al., 2015; Morris et al., 2005; Romero et al., 2013; Smith, Lange, & Huston, 2012). Research by Beer et al. (2010) and Smith et al. (2012) showed a significant correlation between student clicks within the online course space and the likelihood of student success in the course. Furthermore, the research of Smith et al. (2012) indicated that certain items within the course were more likely to predict student success. While Calafiore and Damianov (2011) found that time spent in the course space by students in general could also be used to predict their performance. More specifically, Falakmasir and Habibi (2010) and He (2013) found that students who participated in live video streams or virtual conferences, particularly those that announced their presence and asked questions, received higher grades in the course. Similarly, studies by Cheng, Paré, Collimore, and Joordens (2011), Romero et al. (2013), and Shaw (2012) showed correlations between students with high levels of discussion board participation and performance in online courses.

The research of Agudo-Peregrina et al. (2014) attempted to bring together the various constructs of interaction and presence in a study using data from student activity logs in the LMS to predict performance. The study had three classifications: agent, frequency, and types of participation. Agent refers to the three interaction types developed by Moore (1989) with the addition of Hillman, Willis, and Gunawardena's (1994) student-to-system interaction. Frequency is related to the adoption of LMS tools and features, such as transmission of content, evaluating students, and computer-based instruction. Finally, participation is described as either active or passive. Agudo-Peregrina et al. (2014) found that active student participation from interactions with other students, the instructor, and interactions related to student assessments were significantly related to student performance in online courses. Although student content interactions were most significant in predicting student achievement, Agudo-Peregrina et al. (2014) asserted that the results support the importance of teaching presence, because content interactions required the encouragement of the instructor.

Very few additional studies have used LMS activity data to analyze the relationship between teacher presence, made visible through various forms of class participation by the instructor, and student participation. Ravenna et al. (2012) in a review of the literature on preservice teachers, found that student engagement and participation in discussion boards increased when the instructor was an active participant in the discussion. Furthermore, the authors cautioned that too much participation on the part of the instructor in discussions or overbearing management of discussions by instructors can actually inhibit student participation (Ravenna et al., 2012). Research by Beer et al. (2010) utilizing LMS data, provides additional support for the findings of Ravenna et al. (2012). In their study of over 90,000 students, Beer et al. (2010) found that students enrolled in courses where the instructor made one or more posts had an increased number of clicks within the LMS and a reduced failure rate. Furthermore, in a case study of six online courses, Ladyshewsky (2013) found a positive correlation between instructor discussion board participation and student satisfaction in a case study comparing online courses. Their research suggests that there may be an optimal amount of interaction with the instructor that supports learning (Beer et al., 2010; Ravenna et al., 2012); as the researchers found that too much instructor participation was correlated to decreased student involvement (Ladyshewsky, 2013; Ravenna et al., 2012).

Bair and Bair (2011) and Ladyshewsky (2013) argued that while students expect active participation by the instructor, the discussion board may be the only place an instructor can make his/her participation visible. Research on academic performance by Campbell (2014) looking at the use of email, He (2013) on using live video streaming, and Ma et al. (2015) on the impact of instructor feedback, contradicts this assumption. Nevertheless, beyond the work of Beer et al. (2010), the majority of studies focus on student participation in the online environment and do not look specifically at potential relationships between instructor participation via tools available in the LMS, such as announcement and discussion boards, and student participation and achievement.

LMS: Changing Learning

Just as online learning has become ubiquitous in higher education, so too has the use of LMSs (Beer et al., 2010; Joksimović et al., 2015; You, 2016). Today's LMSs help universities and colleges meet the demand of a virtual student body (Macfadyen & Dawson, 2010), and provide the technologies necessary to facilitate social and constructivist learning methodologies in the online classroom (Beer et al., 2010; Macfadyen & Dawson, 2010; Wei, Peng, & Chou, 2015). However, as a result of the wide spread adoption of LMSs, the development of learning experiences has become somewhat prescriptive because these applications force course development into predefined molds around particular technologies or LMS functionality (Beer et al., 2010). Beer et al. (2010) argued that LMSs are changing teaching strategies and that the change is likely affecting how students engage in learning. For example, in online learning environments students are often required to interact with content and other learners without any prompting from an instructor, a process which can affect motivation and engagement. Additionally, learners typically have open access to instructional content allowing repeated viewing of lectures and extended time to compose questions and discussion responses. A large degree of flexibility, predictability, and simplicity is necessary for large institutions to provide online learning opportunities at scale using mostly their existing resources (Moore & Kearsley, 2011).

In addition to scalability, the adoption of LMSs presents new opportunities to explore how a diverse student body learns. Beer et al. (2010) asserted:

> The almost global adoption of learning management systems as a technical solution to e-learning within universities and their ability to record and track user behavior provides the academy with an unprecedented opportunity to harness captured data relating to student engagement. (p. 75)

Universities are working to combine learning data from the LMS with student demographic data in support of predictive learning analytics. One of the main goals for analytics in higher education is to attract, retain, and successfully graduate students who are properly prepared for the workforce (Johnson et al., 2015). Research in the field on LMS activity logs and data analytics is still in its infancy, and institutions of higher education are novice users of data analytics (Johnson et al., 2015; You, 2016). Nonetheless, there are many efforts underway in higher education to understand and make use of the massive amounts of data captured by instructional systems to inform institutional decision making, instruction, and student agency (Johnson et al., 2015).

LMSs capture detailed information on user activity within the system, such as logins, user clicks, time online, page views, discussion posts, assignment submissions, and more (Agudo-Peregrina et al., 2014; Beer et al., 2010; Lockyer, Heathcote, & Dawson, 2013; Ma et al., 2015; Macfadyen & Dawson, 2010). These data are typically referred to as activity or trace logs (Agudo-Peregrina et al., 2014) and are a direct, unbiased, representation of user activity (Lockyer et al., 2013). Log information can be mined from the LMS, using educational data mining techniques, and then combined with information from other learning systems, such as the student information system (SIS), for learning analytics (Agudo-Peregrina et al., 2014; Peña-Ayala, 2014). The resulting data can be used to inform institutional decisions and efforts to improve the learning experience (Beer et al., 2010; Peña-Ayala, 2014).

Agudo-Peregrina et al. (2014) asserted, "the most basic unit of learning data in the [LMS] for learning analytics is the interaction, but there is no consensus yet on which interactions are relevant for effective learning" (p. 542). Even though LMSs make it easier to identify and quantify various types of interaction (Agudo-Peregrina et al., 2014), data mining efforts designed to understand the interactions of learners in the LMS are scant in the current literature (Mohamad & Tasir, 2013). This is partially due to the enormous amounts of data in the LMS, which can be difficult to access and organize into a manageable format (Beer et al., 2010; Ma et al., 2015). Additionally, the skills necessary for learning analytics development are often not available to higher education institutions. While many LMSs have out-of-the-box reports, most institutions find prepopulated reports limited in their ability to help answer specific institutional questions; often generating more questions than answers (Psaromiligkos et al., 2011).

Nonetheless, interest in and research utilizing data mining and learning analytics is growing (Agudo-Peregrina et al., 2014). Johnson et al. (2015) stated that learning analytics are "still evolving and gaining traction" (p. 26). The authors opined in the 2015 Horizon Report that learning analytics is the focus of much research in higher education (Johnson et al., 2015). For example, Beer et al. (2010), Agudo-Peregrina et al. (2014), Macfadyen and Dawson (2010), and You (2016) used various indicators of learner and instructor activity to predict academic performance. Beer et al. (2010) suggested that the LMS facilitates the interactions that make student engagement possible and the log files on these interactions make visible and measureable elements of student engagement. The authors went on to argue that an approximation of student engagement can be measured based on their participation within an LMS in relation to their grades (Beer et al., 2010). Different modes and/or degrees of participation can then be used to predict the academic performance of future students in such a way that timely interventions on the students' behalf can be pursued (Beer et al., 2010; Lockyer et al., 2013; Macfadyen & Dawson, 2010; Peña-Ayala, 2014). If teaching presence was found to affect student learning outcomes, such interventions might include strategies to increase learner-instructor interactions.

It is important to note that several researchers have cautioned against institutional practices that use LMS data without consideration of learning frameworks (Gašević et al., 2016; Gašević, Dawson, & Siemens, 2015; Javadi & Rajandran, 2013; You, 2016). Course design, tool use, grading criteria, and instruction have implications on learner activities within a course and can therefore affect the predictive strength of models without proper context. Gašević et al. (2016) found that predictive models developed from aggregated activity log data often overestimated or underestimated student achievement when compared to data from specific course subjects, such as math verses communication. Based on their findings, the authors suggest the application of learning analytics that utilize activity logs at a more granular course or program level, or to only include variables generic to the application, such as logins or clicks.

The popularity of LMSs to facilitate and document learning experiences in higher education results in extensive data on the various activities of learners and instructors that represent learning online (Agudo-Peregrina et al., 2014; Beer et al., 2010; Lockyer et al., 2013; Ma et al., 2015; Macfadyen & Dawson, 2010). As the research of Agudo-Peregrina et al. (2014), Beer et al. (2010), and You (2016) have demonstrated, log data from the LMS on user participation in the online environment could provide new insights into the relationship between teacher presence, interaction, and learners, as well as learner participation and academic achievement.

Conclusions and Gaps in Current Research

Technology has evolved since the initial development of the theories and frameworks of Moore (1989, 1993) and Garrison et al. (2000). However, the core principles of their ideas, and the findings of research they have spurred to this day, persist. Current research using available LMS activity log data has continued to show positive correlations between student participation and academic achievement (You, 2016, p. 2). The consensus in the literature is that student participation online, be it course access, clicks, or discussion board posts, correlates to improved academic achievement (Agudo-Peregrina et al., 2014; Beer et al., 2010; Calafiore & Damianov, 2011; Falakmasir & Habibi, 2010; Gašević et al., 2016; He, 2013; Henrie et al., 2015; Joksimović et al., 2015; Lockyer et al., 2013; Macfadyen & Dawson, 2010; Peña-Ayala, 2014; Shaw, 2012; Smith et al., 2012; Wise et al., 2013; You, 2016).

Some literature utilizing LMS data has shown that instructors play a vital role in facilitating and encouraging student participation (Kim et al., 2016; King & Tanner, 2015; Ladyshewsky, 2013; Ravenna et al., 2012). However, research in this area is more limited and less conclusive. In a study completed in 2015 on the use of analytics by instructors, van Leeuwen, Janssen, Erkens, and Brekelmans (2015) found that having learning data available to them led instructors to reach out to students more often. However, the researchers lamented that "the question is whether more teacher interventions are beneficial for the collaboration between students" (van Leeuwen et al., 2015, p. 91). Moreover, much of the current literature relies on discussion board interactions by the instructor and students, with only antidotal inferences of increases of other forms of participation, such as logins, clicks within the course, and time spent in a course as a result of instructor participation. It is this gap in the literature that this study begins to address by more thoroughly analyzing the relationship between instructor participation and that of student in online courses.

CHAPTER III

METHODOLOGY

This study was designed to explore the relationship between instructor participation in online courses and the participation of their students. Furthermore, this study examined if there is a relationship between instructor and student participation and a student's academic performance. User activity log data from the LMS was used to represent specific instructor and student participation behaviors including course logins, clicks in the course, time spent in the course, and participation on the discussion board. Frequency of instructor announcements is also included. Several attribute variables were collected from the student information system on the users included in this study. The attribute variables - student gender, age, prior credits completed, and area of study, were included to analyze any influence on participation. The following chapter describes in greater detail the study's research variables, population, data collection, and data analysis.

Population and Sample

This study is a census of master's level graduate students and instructors, participating in an online course within the spring 2017, summer 2107, fall 2017, and winter 2018 quarters at a small, not-for-profit university in Seattle, WA. Although the university does offer classes at various international locations, this study includes only 10-week domestic online courses because the use of Blackboard and specific tools identified for this study are more consistently employed. Additionally, similar instructional strategies are required with this population (Gašević et al., 2016; Gašević et al., 2015; You, 2016). For example, all domestic online courses require instructors to post announcements on a regular basis and grade student participation on discussion boards (City University of Seattle, 2013). The study includes approximately 550 courses and instructors, and 3,000 students (this is an average based on the spring 2017 term).

Variables Analysis

The instructors, courses, students, and number of instructor announcements and discussion board posts are the independent variables. The number of student logins, time in the course, number of clicks within the course, number of discussion board posts, and students' course grade are the dependent variables. Each student in course is represented by a unique identification (ID) number. The dependent and independent variables associated with the unique ID are scale. Attribute variables are a subset of the independent variables and include student gender, number of credits completed at the start of the course, school affiliation, and age at the beginning of the course. Gender and school affiliation are nominal variables. While, age range and number of credits completed are ordinal and scale variables, respectively. The study was designed to determine if a relationship exists between independent and dependent variables as well as if that relationship varied depending on student age, gender, credits completed, or course subject taken. For greater detail on this study's variables, including variable levels, please see the Variables Analysis in Appendix C.

Procedure

The study required Institutional Research Board (IRB) approval from two universities before data collection could begin. The data used in the study existed within the participating university's systems. No collection instrument was necessary, and participants were anonymized to ensure they would not be compromised any way. To collect the data, the researcher worked with the participating institution's Information Technology department to develop a database query for two systems - the PeopleSoft student information system (SIS) and the learning management systems MySQL database. The resulting data was transformed in Microsoft Excel before import into SPSS. SPSS was used to run a series of analyses to examine potential relationships between the dependent and independent variables. The following section provides detailed information and steps taken in the collection and analysis.

IRB Approval and Data Security

Due to the location and nature of this study, the researcher obtained IRB approval from the University of Tennessee at Chattanooga, the university of record for the dissertation, and the university from which the data was collected. Although the study does not actively involve human subjects, the research design uses archival data collected from human subjects. Accordingly, all personally identifiable information included in the study's dataset were removed. Unique identification numbers were assigned during the query's extraction to Excel to represent each student within a course in the dataset used for analysis. The original course, student, and instructor IDs were backed-up in a separate reference table available only to the Director of IT, at the participating institution, during the course of the study. Data provided to the researcher continues to be stored on a password protected personal drive.

As required by the Office of Human Research Protections (2009), all data related to this study will be kept in a secure location for 3-years after the completion of the study. After 3-years all unpublished research data, excel worksheets, and SPSS files will be destroyed and scrubbed from the researcher’s computer.

Data Collection

The study location’s student information system (SIS), PeopleSoft (PS), and a local MySQL copy of data from Blackboard’s open database were the primary sources of data for this study. A query of PS, based on the identified population, was used to determine the courses, instructors, and students to be included in the study. The dependent variable, students’ final grades, and subset of attribute variables, student gender, age, school affiliation (School of Education, Applied Leadership, Management, or Washington Academy of Language), and number of credits completed at the time of the course start, were included in the PS query results.

Courses identified in the SIS data retrieval were used to query the Blackboard MySQL database. While this database represents several years’ worth of user activity within the LMS, only course activity from the courses identified via the SIS query was collected. The open database provided information on independent variables associated with instructor activity, including number of course announcements and discussion board posts, as well as the dependent variables student logins, number of clicks within a course, total time in a course, and number of discussion board posts.

Figure 3 provides an overview of the model used to collect data from the PeopleSoft SIS and the Blackboard MySQL database. The PS query identified courses based on location, course level (graduate), and instructional mode (online). Instructors, students, and student attribute variables were included in the resulting report. Course IDs from the PeopleSoft report were used in the query of Blackboard's MySQL database to extract user activity data to include in the resulting report.

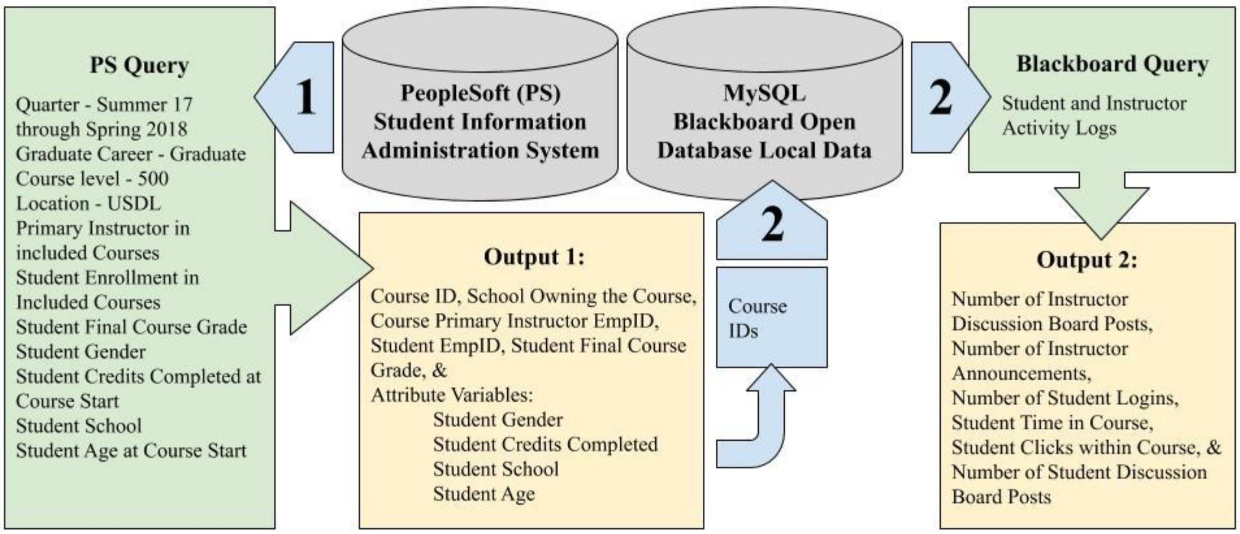

Figure 3 Data collection model shows query of PeopleSoft and Blackboard's MySQL database and its resulting outputs.

Instructor and student ID numbers were used to match users to their role within the course (instructor verse student), their course activities identified above, and their associated attribute variables (student records only) which resulted in one combined report. Figure 4 is an example of one line of data in the resulting report. Data transformations, such as numerical values for nominal values like gender, were completed in Excel.

Column 1	Column 2	Column 3	Column 4	Column 5	Column 6	Column 7
Unique ID DEIDENTIFIED	Course School	# of Instructor Announcements	# of Instructor Discussion Board Posts	Student School	Student Gender	Student Age
Eg. 11822357	Eg. SOM	Eg. 20	Eg. 32	Eg. SAL	Eg. M	Eg. 34

Column 8	Column 9	Column 10	Column 11	Column 12	Column 13
Student Number of Credits Complete	Student Course Grade	# of student Logins	Student time in the course	# of student clicks within the Course	# of student Discussion Board Posts
Eg. 24	Eg. 3.25	Eg. 104	Eg. 4,320 min.	Eg. 987	Eg. 30

Figure 4 Example of resulting data report fields from the data pull described in Figure 3.

As Figure 4 indicates, each row in excel represents one student in a specific course, their aggregated participation components, and the instructor's aggregated announcements and discussion board posts within the same course. The same student likely appears in the report more than once, as students often enroll in more than one course a quarter, and within multiple courses over four quarters. This is a delimitation of this study; each student in a course appears as a unique individual with an unduplicated identification number. Gender and age group of students likely did not change from quarter to quarter. However, student credits completed did change, and school affiliation may have also changed over the course of a year. Therefore, each row representing one student in a course included all attributional data. This was part of deidentifying students included in the study, preventing access to identifiable information outside the participating institution.

Research Design and Analysis

This was a non-experimental correlational research study (Patten, 2012) that was designed to determine if there is any relationship between faculty participation in online courses and students’ participation and performance within the same course. This study utilized quantitative data from the LMS that represented faculty and student online course and content access, time in the course, and contributions in the form of discussion board post and announcements (instructors only). Attributional data from the student information system was included for population description and deeper analysis of relationships with participation.

As suggested by Field (2009), descriptive statistical tests were completed to describe the characteristics of the dataset and determine the appropriate tests. Regression analyses were completed on each of the predicted variables related to student participation – course access, time in course, clicks within the course, student discussion board posts, and student achievement to answer the first five research questions in this study. The independent variables, number of instructor announcements and discussion board posts, as well as attribute variables, student age, gender, and credits completed, were included as predictors in each regression analysis (Field, 2009).

Students at the participating institutions may take a course within their school of enrollment or from another school. Often elective courses were taken outside the student’s school of enrollment. Additionally, some academic subjects may lend themselves to greater student participation in the online classroom (Joksimović et al., 2015). To look more closely at the relationship between a student, the school in which they were taking an online course, and the students’ participation in the course, as described in research question six, two multivariate analyses of variance (MANOVA) tests were completed. Independent variables were created to divide the dataset into groups based on the school in which the student was enrolled and then again by the school the course belonged to – School of Management, School of Applied Leadership, School of Education, and Washington Academy of Language. These school groupings were used in the MAVOVA tests to examine differences in student participation (student logins, clicks within the course, time in the course, number discussion board posts, and student achievement) based on school of enrollment or the affiliation of a course to a school (Field, 2009).

Summary

The research methods used in this study were selected to facilitate the accurate and ethical collection of mass amounts of archival, quantitative data from the participating university, given a set of controlled parameters. The researcher outlined the steps for collecting the data, which were vetted by the participating institution's Directors of Information Technology and the Office of Institutional Effectiveness. Furthermore, the proposed data analysis strategy was identified in advance, as required for research approval, but later minimally refined as necessary for the resulting data to be analyzed. Research processes and strategies have been provided in an effort to assist other researchers to analyze data from similar systems to answer comparable research questions.

CHAPTER IV

RESULTS

The purpose of this study was to analyze the relationship between instructor announcements and discussion board posts in an online class and student activity and achievement within the course. The study included the following components representing student participation within an online course: (1) number of times a student accessed a course, (2) the number of clicks a student made within a course, (3) the time a student spent within a course, and (4) the number of discussion board posts a student made within a course. Student gender, age, and prior credits completed were also considered in relationship to student online course activity. In order to examine possible relationships to field of study or course subject, students were divided into groups based on school of enrollment as well as school owning the course taken (course school).

Descriptive statistics show that the resulting population included 2,669 cases. Cases are one student in a course and do not represent unique students, as one student could be included two or more times depending on the number of courses they took over the year represented in the data. Of the included cases, 53.4% were female and 46.6% were male. The average age was 37.55 with the youngest participants being 21 and the oldest 65. Gender and age in data are representative of IPEDs and data provided by data analysts at the study location (A. L. Portwood & S. D. Sullivan, personal communication, February 29, 2020). An average of 22.24 credits were completed by the learners prior taking the course included in the study, with the lowest number of credits being zero and 139 being the most credits completed. The majority of students were enrolled (*N* = 2,162) and taking classes (*N* = 2,085) in the School of Management, followed by the School of Education (*N* = 247 enrolled, *N* = 239 taking classes), the School of Leadership (*N* = 242 enrolled, *N* = 300 taking classes), and finally the Washington Academy of Language (*N* = 18 enrolled, *N* = 45 taking classes).

Research Questions One and Two

A multiple regression was used to analyze the relationship between the number of student course accesses and the independent variables, number of instructor discussion board posts and course announcements. Attribute variables of student age, gender, and prior credits completed were also included as independent variables. As prescribed by Lund Research Ltd. (2018) the following regression assumptions were reviewed and inform the results provided. The data met the assumption of linearity as assessed by partial regression plots and a plot of studentized residuals against the predicted values. Data had independence of residuals, as assessed by a Durbin-Watson statistic of 1.005. Data had homoscedasticity, as assessed by visual inspection of a plot of studentized residuals versus unstandardized predicted values. Data presented no evidence of multicollinearity, as assessed by tolerance values greater than 0.1. There were 42 cases with studentized deleted residuals greater than ±3 standard deviations, but no leverage values greater than 0.2, or values for Cook's distance above 1. The assumption of normality was met, as assessed by a Q-Q Plot. The multiple regression model was statistically significant and predicted the number of student course accesses, $F(5, 2663) = 19.046$, $p < .001$, adj. $R2 = .033$. Instructor announcements and student age contributed significantly to the prediction, $p < .001$. Regression coefficients and standard errors are shown in Table 4.1.

Table 4.1 Summary of Multiple Regression Analysis for Number of Student Course Accesses

Variable	*B*	SE_{β}	β	p
Instructor Discussion Posts	0.025	0.018	0.029	.154
Instructor Announcements	0.635	0.118	0.107	.000
Age	0.853	0.111	0.148	.000
Gender	1.041	2.078	0.01	.616
Prior Credits Completed	-0.074	0.062	-0.023	.233

A second multiple regression was run to analyze the relationship between number of student clicks within a course and the independent variables, the number of instructor discussion board posts and course announcements. Attribute variables of student age, gender, and prior credits completed were also included as independent variables. The data met the assumption of linearity as assessed by partial regression plots and a plot of studentized residuals against the predicted values. Data had independence of residuals, as assessed by a Durbin-Watson statistic of 0.722. Data had homoscedasticity, as assessed by visual inspection of a plot of studentized residuals versus unstandardized predicted values. Data presented no evidence of multicollinearity, as assessed by tolerance values greater than 0.1. There were 72 cases with studentized deleted residuals greater than ±3 standard deviations, but no leverage values greater than 0.2, or values for Cook's distance above 1. The assumption of normality was met, as assessed by a Q-Q Plot. The multiple regression model was statistically significant and predicted the clicks within the course, $F(5, 2663) = 23.802$, $p < .001$, adj. $R2 = .041$. All variables, except gender, contributed significantly to the prediction, $p < .05$. Regression coefficients and standard errors are shown in Table 4.2.

Table 4.2 Summary of Multiple Regression Analysis for Number of Student Clicks within a Course

Variable	*B*	SE_{β}	β	p
Instructor Discussion Posts	0.025	0.018	0.029	.000
Instructor Announcements	0.635	0.118	0.107	.000
Age	0.853	0.111	0.148	.034
Gender	1.041	2.078	0.01	.744
Prior Credits Completed	-0.074	0.062	-0.023	.037

The multiple regression process was repeated to analyze the relationship between a student's time within a course and the independent variables, the number of instructor discussion board posts and course announcements. Attribute variables of student age, gender, and prior credits completed were also included as independent variables. The data met the assumption of linearity as assessed by partial regression plots and a plot of studentized residuals against the predicted values. Data had independence of residuals, as assessed by a Durbin-Watson statistic of 1.106. Data had homoscedasticity, as assessed by visual inspection of a plot of studentized residuals versus unstandardized predicted values. Data presented no evidence of multicollinearity, as assessed by tolerance values greater than 0.1. There were 51 cases with studentized deleted residuals greater than ±3 standard deviations, but no leverage values greater than 0.2, or values for Cook's distance above 1. The assumption of normality was met, as assessed by a Q-Q Plot. The multiple regression model was statistically significant and predicted the students time within the course, $F(5, 2663) = 35.629$, $p < .001$, adj. $R2 = .061$. All variables, except gender, contributed significantly to the prediction, $p < .001$. Regression coefficients and standard errors shown in Table 4.3.

Table 4.3 Summary of Multiple Regression Analysis for Student Time within a Course

Variable	*B*	SE_{β}	β	p
Instructor Discussion Posts	3.651	0.918	0.079	.000
Instructor Announcements	33.459	6.126	0.107	.000
Age	57.169	5.758	0.188	.000
Gender	206.754	108.021	0.036	.056
Prior Credits Completed	-15.775	3.212	-0.093	.000

A final multiple regression was run in this series to analyze the relationship between number of student discussion board posts within a course and the independent variables, the number of instructor discussion board posts and course announcements. Attribute variables of student age, gender, and prior credits completed were also included as independent variables. The data met the assumption of linearity as assessed by partial regression plots and a plot of studentized residuals against the predicted values. There was independence of residuals, as assessed by a Durbin-Watson statistic of 1.3., as well as homoscedasticity, as assessed by visual inspection of a plot of studentized residuals versus unstandardized predicted values. Data presented no evidence of multicollinearity, as assessed by tolerance values greater than 0.1. There were 32 cases with studentized deleted residuals greater than ±3 standard deviations, but no leverage values greater than 0.2, or values for Cook's distance above 1. The assumption of normality was met, as assessed by a Q-Q Plot. The multiple regression model was statistically significant and predicted the number of student discussion board posts, $F(5, 2663) = 71.562$, $p < .001$, adj. $R2 = .0117$. All variables except prior credits completed contributed significantly to the prediction, $p < .05$. Regression coefficients and standard errors are shown in Table 4.4.

Table 4.4 Summary of Multiple Regression Analysis for Number of Student Discussion Board Posts in a Course

Variable	*B*	SE_{β}	β	p
Instructor Discussion Posts	0.07	0.007	0.201	.000
Instructor Announcements	0.265	0.045	0.113	.000
Age	0.573	0.042	0.251	.000
Gender	-2.009	0.788	-0.047	.011
Prior Credits Completed	0.034	0.023	0.027	.147

Research Questions Three and Four

A multiple regression was used to analyze the relationship between a student's course grade and the independent variables, the number of instructor discussion board posts and announcements. Attribute variables of student age, gender, and prior credits completed were also included as independent variables. The data met the assumption of linearity as assessed by partial regression plots and a plot of studentized residuals against the predicted values. There was independence of residuals, as assessed by a Durbin-Watson statistic of .907, as well as homoscedasticity, as assessed by visual inspection of a plot of studentized residuals versus unstandardized predicted values. Data presented no evidence of multicollinearity, as assessed by tolerance values greater than 0.1. There were 108 cases with studentized deleted residuals greater than ±3 standard deviations, but no leverage values greater than 0.2, or values for Cook's distance above 1. The assumption of normality was not met, as assessed by a Q-Q Plot. The multiple regression model was statistically significant and predicted students' course grade, $F(5, 2663) = 7.0111$, $p < .001$, adj. $R2 = .011$. Only gender and prior credits completed contributed significantly to the prediction, $p < .05$. However, readers should keep in mind the limitations of interpretation under the conditions where all assumptions are not met. Regression coefficients and standard errors are shown in Table 4.5.

Table 4.5 Summary of Multiple Regression Analysis for Student Grade with a Course

Variable	*B*	SE_{β}	β	p
Instructor Discussion Posts	-3.33E -05	0	-0.002	.903
Instructor Announcements	-0.003	0.002	-0.038	.060
Age	0.003	0.002	0.03	.126
Gender	-0.141	0.032	-0.085	.000
Prior Credits Completed	0.003	0.001	0.052	.007

Research Question Five

One final multiple regression was run to analyze the relationship between students' course grade and the independent variables representing student participation within a course. Attribute variables of student age, gender, and prior credits completed were also included as independent variables. The data met the assumption of linearity as assessed by partial regression plots and a plot of studentized residuals against the predicted values. There was independence of residuals, as assessed by a Durbin-Watson statistic of .811, as well as homoscedasticity, as assessed by visual inspection of a plot of studentized residuals versus unstandardized predicted values. Data presented no evidence of multicollinearity, as assessed by tolerance values greater than 0.1. There were 108 cases with studentized deleted residuals greater than ±3 standard deviations, but no leverage values greater than 0.2, or values for Cook's distance above 1. The assumption of normality was met, as assessed by a Q-Q Plot. The multiple regression model was statistically significant and predicted student's course grade, $F(7, 2661) = 45.623$, $p < .001$, adj. R2 = .105. Five of the seven variables contributed significantly to the prediction, $p < .05$. Student clicks within a course and time within a course did not significantly contribute to the prediction. Regression coefficients and standard errors are shown in Table 4.6.

Table 4.6 Summary of Multiple Regression Analysis for Student Participation

Variable	*B*	SE_{β}	β	p
Number of Student Course Accesses	.002	.000	.132	.000
Student Clicks within a Course	5.446E-7	.000	.033	.109
Student Time within a Course	-1.155E-6	.000	-.004	.873
Student Discussion Board Posts	.009	.001	.233	.000
Prior Credits Completed	.003	.001	.057	.002
Student Age	-.004	.002	-.042	.029
Student Gender	-.141	.031	-.085	.000

Research Question Six

A one-way multivariate analysis of variance (MANOVA) was used to determine the effect of a student's field of study on course participation. Student school, including School of Education (SOE), School of Leadership (SAL), School of Management (SOM), and School of

Language (WAL), was used as a proxy for field of study. Number of student course access, time in course, clicks within the course, and discussion board posts represented student participation. Data did not meet the assumptions of outliers, normality, homogeneity of variance, or multivariate outliers. However, there was no multicollinearity as assessed by Pearson correlation ($r = .393$, $p = .002$), and scatterplots showed linear relationships between dependent variables in each school except WAL. Although several assumptions were not met, MANOVA is a robust test (Lund Research Ltd., 2018) and the dataset is large, with 2,669 cases, adding to the strength of the results (Field, 2019). Despite this, readers are cautioned keep these violations of assumptions in mind when considering test results. There was a statistically significant difference between the schools on the combined dependent variables, $F(15, 7989) = 25.417$, $p < .0005$; Pillai's Trace = .137; partial $\eta 2 = .046$.

As a follow up to the statistically significant result of the MANOVA, univariate ANOVAs were used to determine the significance of each dependent variable. ANOVAs showed that each variable was also statistically significant within each student's school of enrollment; student course grade, $F(3, 2665) = 8.950$, $p < .001$; partial $\eta 2 = .010$; student clicks within a course, $F(3, 2665) = 63.324$, $p < .001$; partial $\eta 2 = .067$; student course accesses, $F(3, 2665) = 25.961$, $p < .001$; partial $\eta 2 = .028$; student minutes within the course, $F(3, 2665) = 25.643$, $p < .001$; partial $\eta 2 = .028$; and student discussion board posts, $F(3, 2665) = 38.787$, $p < .001$; partial $\eta 2 = .042$. Results of each univariate ANOVA are reported in Table 4.7.

Table 4.7 Univariate ANOVA results for Student School of Enrollment

Source	Dependent Variable	*df*	F	p	Partial Eta Squared
Student School	Student Course grade	3	8.950	.000	.010
	Student clicks within a course	3	63.324	.000	.067
	Student course accesses	3	25.961	.000	.028
	Student minutes within the course	3	25.643	.000	.028
	Student discussion board posts	3	38.787	.000	.042

In support of the findings, given a possible violation of the assumption of homogeneity of variance, a Game-Howell post hoc test was used to compare all combinations of group differences. The tests revealed a significant difference in course grades between SOE and both SAL and SOM, the number of student course accesses in SOE and WAL compared to that in SOM and SAL, the number of student clicks within SOM and WAL courses compared to all other schools, the time students spend in an online course in SOE compared to SAL and SOM, as well as significant differences between SOM and WAL, and the number of discussion board posts students make in SOE and WAL compared to SOM and SAL. Table 4.8 shows the results of each Game-Howell comparison.

Table 4.8 Game-Howell post hoc test for Student School of Enrollment

Dependent Variable	(I) Student School	(J)Student School	Mean Difference (I-J)	SE
Student Course grade	SAL	SOE	±.241*	.0630
		SOM	±.043	.0528
		WAL	±.179	.2277
	SOE	SOM	±.284*	.0430
		WAL	±.420	.2257
	SOM	WAL	±.136	.2230
Student clicks within a course	SAL	SOE	±3339.28	1795.579
		SOM	±30499.32*	1803..562
		WAL	±13148.85*	1718.601
	SOE	SOM	±33838.61*	1590.966
		WAL	±9809.57*	1493.964
	SOM	WAL	±43648.18*	1503.5449
Student course accesses	SAL	SOE	±26.06*	3.534
		SOM	±4.55	3.316
		WAL	±27.13*	6.519
	SOE	SOM	-30.61*	2.106
		WAL	±1.07	5.995
	SOM	WAL	±31.68*	5.869
Student minutes within the course	SAL	SOE	±1619.33*	208.047
		SOM	±3.23	197.507
		WAL	±1278.06	469.888
	SOE	SOM	±1622.57*	110.638
		WAL	±341.27	440.484
	SOM	WAL	±1281.30*	435.605
Student discussion board posts	SAL	SOE	±13.25*	1.444
		SOM	±1.42	1.185
		WAL	±14.88*	3.043
	SOE	SOM	±14.67*	1.065
		WAL	1.64	2.998
	SOM	WAL	±16.30*	2.882

To determine the effect of school subject – business, leadership, education, languages - on course participation, a one-way multivariate analysis of variance (MANOVA) was used. The school in which a course was offered, regardless of students' field of study, was used as a grouping mechanism, and student course access, time in course, clicks within the course, and discussion board posts represented participation. Data did not meet the assumptions of outliers, normality, homogeneity of variance, or multivariate outliers. However, there was no multicollinearity as assessed by Pearson correlation ($r = .393$, $p = .002$) and scatterplots showed linear relationships between dependent variables in each school except for course grade in the schools of language (WAL) and education (SOE). The violation of several assumptions should be weighted into any interpretation of results. That said, as with the student school MANOVA, the robustness of the test and the size of the dataset act to offset the impact of assumption violations. There was a statistically significant difference between the schools on the combined dependent variables, $F(15, 7989) = 31.992$, $p < .0005$; Pillai's Trace = .170; partial $\eta 2 = .057$.

Univariate ANOVAs showed that each dependent variable was also statistically significant within each course school; student course grade, $F(3, 2665) = 11.449$, $p < .001$; partial $\eta 2 = .013$; student clicks within a course, $F(3, 2665) = 81.751$, $p < .001$; partial $\eta 2 = .084$; student course accesses, $F(3, 2665) = 29.191$, $p < .001$; partial $\eta 2 = .032$; student minutes within the course, $F(3, 2665) = 27$, $p < .001$; partial $\eta 2 = .029$; and student discussion board posts, $F(3, 2665) = 46.846$, $p < .001$; partial $\eta 2 = .050$. The results of each univariate ANOVA are provided in Table 4.9.

Table 4.9 Univariate ANOVA results for Course School

Source	Dependent Variable	*df*	F	p	Partial Eta Squared
Course School	Student Course grade	3	11.449	.000	.013
	Student clicks within a course	3	81.751	.000	.084
	Student course accesses	3	29.191	.000	.032
	Student minutes within the course	3	27.000	.000	.029
	Student discussion board posts	3	46.846	.000	.050

In support of the findings, given a possible violation of the assumption of homogeneity of variance, a Game-Howell post hoc test was used to compare all combinations of group differences. The tests revealed a significant difference in course grades between SOE and both SAL and SOM, the number of student course accesses in SOE and WAL compared to that in SOM and SAL, the number of student clicks within SOM and WAL courses compared to all other schools, and the time students spend in an online course and the number of discussion board posts they make in SOE and WAL compared to SOM and SAL. Table 4.10 shows the results of each Game-Howell comparison.

Table 4.10 Game-Howell post hoc test result for Course School

Dependent Variable	(I) Student School	(J)Student School	Mean Difference (I-J)	SE
Student Course grade	SAL	SOE	±.379*	.0622
		SOM	±.070	.0543
		WAL	±.161	.1165
	SOE	SOM	±.309*	.0401
		WAL	±.218	.1106
	SOM	WAL	±.091	.1063
Student clicks within a course	SAL	SOE	±2103.93	1411.990
		SOM	±32757.18*	1428.252
		WAL	±14068.04*	97.945
	SOE	SOM	±34861.11*	1636.394
		WAL	±11964.11*	1257.998
	SOM	WAL	±46825.22*	1276.224
Student course accesses	SAL	SOE	±27.55*	3.432
		SOM	±3.02	3.195
		WAL	±33.37*	4.131
	SOE	SOM	±30.57*	2.149
		WAL	±5.82	3.387
	SOM	WAL	±36.39*	3.147
Student minutes within the course	SAL	SOE	±1623.49*	199.068
		SOM	±18.79	187.529
		WAL	±1292.08*	271.436
	SOE	SOM	±1642.27*	112.533
		WAL	±331.41	226.216
	SOM	WAL	±1310.86*	216.132
Student discussion board posts	SAL	SOE	±13.30*	1.323
		SOM	±1.44	1.022
		WAL	±18.59*	1.956
	SOE	SOM	±14.74*	1.088
		WAL	±5.30*	1.991
	SOM	WAL	±20.04*	1.806

Summary

Student participation, represented by the number of student course accesses, clicks within a course, discussion board posts, and student time within a course, are significantly related to the number of instructor announcements. Instructor discussion board posts were also significantly related to all components of student participation included in the study, except the number of student course accesses. The attribute variable, student age, was significantly related to the components of student participation examined in this study to varying degrees. As student age increased, participation also increased. It is important to note that each ANOVA test of student participation had several cases of studentized residuals greater and/or less than three; failing to meet the assumption of homoscedasticity (Lund Research Ltd., 2018). However, the results of the test can still be considered significant due to the size of the sample (Field, 2009) as well as the robustness of the ANOVA test (Lund Research Ltd., 2018).

Additionally, the number of student course accesses and student discussion board posts were found to have a significant relationship to students’ grades within a course. However, even though the number of instructor announcements and discussion board posts had a significant relationship to student participation, no significant relationship was found between these forms of instructor participation and students’ grades within a course. The ANOVA test used to explore the relationship between student grades and their course participation failed to meet the assumption of linearity. Similarly, the ANOVA used to analyze the relation between instructor participation and student grades failed to meet the assumption of normality. Here again, the size of the sample and the robustness of the ANOVA test may be enough to overcome the failure to meet some assumptions (Field, 2009; Lund Research Ltd., 2018).

The last two analyses compared differences between school groups. The first grouped student participation results by the school in which the student was enrolled. The second grouped student participation results by the school owning the course taken. The results of the MANOVA analyses supported significant differences between school of enrollment as well as school course owner. However, there were only minor differences between the results of students grouped by enrollment and the groups based on school course owner. The Game-Howell comparison test shows that significant differences are consistently observed between the School of Education (SOE) and the Schools of Applied Leadership (SAL) and Management (SOM), regardless of the grouping mechanism. The Washington Academy of Language (WAL) is also often significantly different from the SAL and the SOM, and to a lesser degree the SOE.

CHAPTER V

DISCUSSION

Higher education is in a period of rapid change (Gopalan, 2016; Lemoine, Seneca, & Richardson, 2019). Pressured by changes in learner characteristics and facilitated by advancements in technology, post-secondary education is experimenting with new approaches to learning and discovering what new strategies may have sustainable potential. New technologies have fueled change while becoming mission critical to many institutions (Beer et al., 2010; Joksimović et al., 2015; You, 2016). The resulting Big Data, making advanced learning analytics possible, provide levels of detail about a student's learning journey that are only just beginning to be analyzed and put to use (Johnson et al., 2015). In such a long-standing tradition, the question persists: how do institutions of higher education identify the best practices to maintain, adopt, or modify in an environment often limited by resource constraints and conditions of funding?

The staying power of online learning in higher education is evident in its wide adoption (Allen & Seaman, 2015). The same technology that enabled distance education continues to evolve and present new opportunities for innovation in secondary education. At the same time, online learning has been a constant in higher education long enough to establish best practices based on research. Frameworks have also been applied and supported for teaching and learning in this new virtual environment.

This research effort was founded on two influential frameworks for supporting learning in online environments: Moore's (1989) three types of interaction and Garrison et all's (2000) community of inquiry. These frameworks build on the early work of Vygotsky (1978) and Bandura (1986) whose theories put forth the importance of social engagement to the learning process. Both frameworks, and the research of many scholars that followed, opine the significant importance of the instructor role to student satisfaction (Enightoola et al., 2014; Kuo et al., 2013), perceived learning (Agudo-Peregrina et al., 2014; Joo et al., 2011; Ma et al., 2015), and active engagement in learning online (Kim et al., 2016; King & Tanner, 2015). Hrastinski (2008, 2009) went so far as to argue that evidence of active engagement by the learner, or participation, is akin to learning. Several studies have supported his theory in their findings of significant relationships between student participation and academic achievement in online courses (Beer et al., 2010; Calafiore & Damianov, 2011; Romero et al., 2013; Shaw, 2012; Smith et al., 2012). However, missing from the literature was substantial evidence of a connection between instructor participation and student participation and academic achievement within an online course. Specifically, does student participation increase as a result of instructor participation and does a student's increase in participation have any correlation to their final results within a course? Furthermore, few research studies utilized objective data on participation contained within LMS logs to support existing literature that, for the majority, was based on subjective data from surveys or observation.

To begin to address this gap in the literature, this study focused on the instructional components of the two frameworks identified above, including Moore's (1989) learner-instructor interaction and Garrison et al's (2013) teaching presence. The focus was further narrowed to a selection of quantifiable and student-observable instructor behaviors, categorized by Anderson et al. (2001) as forms of direct instruction and facilitation of discourse. For the purpose of this study, instructor course announcements and discussion board posts were used within these categories. LMS log data were used to collect identified instructor participation components as well as several data points used as proxy for student participation; including student course accesses, time in the course, course clicks, and discussion board posts. This extracted LMS data as well as students' course grades from the SIS were used in the analyses of the relationship between instructor participation and student participation and achievement in online, graduate level courses.

Of additional importance to the literature, the research design demonstrates how LMS log data can be used to shed additional light on the online learning environment. Log data can provide different insights into the activities of instructors and students, and their potential relationship to student learning. Student attribute variables, including credits completed, age, and gender, extracted from the SIS, were combined with the LMS data. The combined data were analyzed in a series of regressions performed in SPSS. The results add to the existing literature and hopefully help to inform effective practices in course design, instructor facilitation, and the actionable use of LMS log data.

The study was guided by six research questions that identify the forms of participation, on the part of the instructor and student, as well as student attribute variables included in the data extractions and analyses. Summarized briefly, the research questions (see Chapter One) stated that the study would analyze the relationship between instructor online course announcements and discussion board posts with student online course accesses, clicks within the course, time in the course, discussion board posts, and student final grade. Whether any relationship varies based on the attribute variables of student age, gender, number of credits completed, school of enrollment, or course discipline was incorporated into each analysis.

Results of the regression analyses were significant in all except the analyses related to questions three and four. Questions three and four examined the relationship between instructor participation and student achievement. While the results indicate a relationship between instructor participation and student participation as well as student participation and their achievement in an online course, no significant relationship was observed between instructor participation and student achievement in the course. In the following section, these results, significant and otherwise, are further discussed and placed in the context of the study to include location, population, and current relevant literature. Recommendations for future research are also shared.

Interpretation of Findings

Several areas in the results stood out as incongruent and needing additional context. The lack of any relationship between instructor participation and student achievement, as well as the effect of age and discipline on reported results pose additional questions in need of investigation. These topics will require research to expound on the results presented in this study. However, the existing literature can, in some cases, provide context and possible explanations for the topics in question. Furthermore, information about policies and practices at the study location can provide some additional insights on select results.

Instructor Participation and Student Achievement

Of particular interest to the researcher is the apparent disconnect in the results that indicate a significant relationship between instructor participation and student participation and student participation and achievement, but no relationship between instructor participation and student achievement. Results indicate a significant relationship between student course accesses, discussion board posts, gender, age, and prior credits completed with learner achievement, but found no significance between instructor participation (announcements nor discussion board posts) and student achievement. While additional research and analysis are needed to better understand this seemingly incompatible result, the existing literature related to self-efficacy, motivation, and learner age give us some potential insights.

Learner self-efficacy and motivation play a vital role in student academic achievement online (Artino & Stephens, 2009; Shea & Bidjerano, 2010; Zimmerman & Schunk, 2001). Shea and Bidjerano (2010) state that self-efficacy "can be viewed as a subjective judgment of one's level of competence in executing certain behaviors or achieving certain outcomes in the future" (p. 1723). Within a similar vein, Trolian, Jach, Hanson, and Pascarella (2016) define motivation as "a student's desire, effort, and persistence related to achieving academic success" (p. 811). The two concepts are intertwined and overlap in the literature, as self-efficacy has been shown to be a predictor of motivation (Bandura & Locke, 2003). Self-efficacious learners demonstrate high achieving characteristics such as course participation, critical thinking, rehearsal, persistence, and seeking help when needed (Artino & Stephens, 2009; Zimmerman & Schunk, 2001). As Bandura's (1994) theory of self-efficacy asserts and further research in online instruction supports, self-efficacy can be encouraged within learners through instructor interaction and course design that supports mastery (Komarraju & Nadler, 2013; Shea &

Bidjerano, 2010). However, the primary factors associated with self-efficacy are inherent in a learner's experiences (personal and vicarious) (Bandura, 1994).

The age of learners enrolled in college courses is another inherent learner characteristic that has been shown to be a predictor of academic achievement; with more mature aged college learners being more likely to have higher academic achievement (Arjomandi, Seufert, O'Brien, & Anwar, 2018; Vella, Turesky, & Hebert, 2016). Older students are often returning to academia by their own choosing and most frequently cite intrinsic motivational factors in their reasons for pursuing education (Francois, 2014). It is not surprising then that self-efficacy also increases with level of education, with graduate students showing higher self-efficacy than undergraduate learners (Artino & Stephens, 2009).

This research study included only online graduate students with an average age of 37.5, higher than the national average at private non-profit institutions (McFarland et al., 2019). As the literature suggests, age can be a factor in learner self-efficacy. Experienced learners more frequently display high achiever behaviors, such as course participation, and are more likely to be successful (Artino & Stephens, 2009; Shea & Bidjerano, 2009; Zimmerman & Schunk, 2001). As stated in Chapter One, there is little literature on the impact of instructor participation on student participation and achievement. Therefore, given the available literature on self-efficacy and learner age/degree level, it is possible that findings that indicate a significant correlation between instructor participation and student participation could be the result of typical high achiever behaviors shown to be associated with more experienced, self-efficacious learners. Simply put, the participation and achievement of the majority of learners in this study would be expected to be high regardless of variations in instructor participation.

Although the majority of research, including studies on MOOCs, supports the importance of teacher presence to the learning experience in online classes (Adamopoulos, 2013; Anderson et al., 2001; Kim et al., 2016; King & Tanner, 2015; Wang & Antonenko, 2017), the results of a few studies assert the limited impact instructors have on student achievement (Campbell, 2014; Tomkin & Charlevoix, 2014). Of particular importance to resolving these different views is the matter of defining teacher presence and instruction for today's learning environment. Specifically, do course design and methods associated with automated instruction (adaptive delivery, recorded lecture, and programmed feedback), which are developed with increasing frequency by curriculum and instruction specialists (Johnson & Samora, 2016), still represent teacher presence as defined in the CoI framework? Several researchers have asserted the need to modify the CoI framework to reflect the importance of learner interaction with technology in this new learning landscape (Hew & Cheung, 2014; Johnson & Samora, 2016). Hillman et al. (1994) argued early in the era of telecommunication that learner-to-technology interaction should be included in online learning frameworks to more accurately represent learner interactions with the learning environment.

Additionally, and of particular application to the graduate population represented in this study, select studies found that the instructional design components of teaching presence - course design and organization - had greater impact on learner satisfaction and learning (Preisman, 2014; Sheridan & Kelly, 2010). Furthermore, Gering, Sheppard, Adams, Renes, and Morotti (2018) found that graduate students reported more value in discussion board interactions with peers than did undergraduate students. This finding is supported by previous research (Chyung, 2007) that found graduate students participate more in discussion boards than undergraduate learners. These findings give credence to the importance of learner-to-learner and learner-to-content interactions (social and cognitive presence) to learning at the graduate level, but also highlight the need for further research on the preferences and needs of students at different academic career levels.

Worth noting, student clicks and time in the online course were not significantly associated with student achievement, unlike the other participation variables included in this study. As Joksimović et al. (2015) suggests, high click counts and time in the course may also indicate student challenges with navigation in the online course environment. Technological challenges with online courses have been associated with non-traditional learners (Benshoff, Cashwell, & Rowell, 2015) but can also be the result of poorly designed courses (Rao, 2012). Due to the common design of courses at the location of the study, the results more likely reflect age related factors, but additional research is necessary to rule out other possibilities.

Grades and Grade Inflation

Researchers have long asserted that student grades, while the most consistently available measure of learning in higher education, are problematic (Marini, Shaw, Young, & Ewing, 2018; Schwab, Moseley, & Dustin, 2018). Course subject, learner characteristics such as course participation, and instructor bias, for example, have been found to impact the reliability of course grades as a measure of learning (Marini et al., 2018). Most researchers agree that using multiple variables associated with learning, such as GPA, employment after graduation, and graduate school admittance for example, would make for more reliable research results. Although this research study used course grades as a proxy for academic achievement, the analyses examined relationships, not the level of grade received. However, it is worth noting that the grades included in this research study, like many grades in higher education (Klafter, 2019), do not exhibit a normal bell curve, but are rather skewed to the upper end of the 4.0 scale with an average of 3.74.

Along with the arguable reliability of grades, their inflation as evident in this study's average grade highlights an area in need of further research. The literature on grade inflation asserts that higher grading is more common at private schools, in soft, applied disciplines, and particularly in classes taught by adjuncts (Marini et al., 2018). Adjunct contract renewals are often linked with positive student evaluations, and students have been found to give higher rating in courses they deem to be easier (Marini et al., 2018). These factors describe the attribute of the study location. Here again, it is possible that student participation had little to do with the grades achieved, as is seen in the relationship between instructor participation and student achievement. To expand upon the results of this study, future research should consider other variables associated with learning, using multiple factors where possible or even a pre/post-test approach if appropriate.

Disciplinary Differences

Data were analyzed in groups based on school of student enrollment and school owning the course. Group size did not change dramatically from school enrollment to school owning the course, with the exception of the Washington School of Languages (WAL), which saw an 85.7% increase. The School of Applied Leadership (SAL) increased 21.4%, and the Schools of Education (SOE) and Management (SOM) decreased 3.3% and 3.6% respectively. It is important to recall that these numbers do not represent enrollment, but are more akin to headcount, representing each student in a course included in this study (i.e. students may be counted one or more times if they enrolled in more than one course within the year represented in the data). The

N for headcount in WAL drops to 18, too small to result in reliable results (Field, 2009). This is perhaps one reason the results of the MANOVA analysis show a significant difference in participation between WAL and the Schools of Management and Leadership, except in student clicks within the course. However, it does not explain why similar differences were identified between SOE and the same schools.

Disciplinary similarities between the Schools of Languages and Education, and differences between these schools and the Schools of Management and Leadership, may shed additional light on the results of this study. First, the courses and students associated with WAL represent one graduate certificate program: Teaching English to Speakers of Other Languages (TESOL). Individuals who complete the TESOL certificate can apply credits directly to one of two Masters in Education programs at the study location (City University of Seattle, 2019). It is fair to say that this teaching certificate is more similar in discipline to education than the other two schools included in the study.

Leadership and Business Verses Education

While the School of Applied Leadership's discipline is also more closely aligned with the SOE (also conferring master's in education), their approach to course delivery is nearly the same as the SOM. The SOM and SAL's courses are delivered entirely asynchronously, relying heavily on discussion boards to cover course content and facilitate learner-to-learner and learner-to-instructor interaction. Both schools also maintained strict guidelines for instructor activity in the online course space, including weekly announcements and interactions on the discussion board (see Appendix D). Conversely, the SOE had no such guidelines, and while all the courses were fully online, some relied less on interaction in the online course space. It was common practice in the SOE to use one-to-one communication through email outside the LMS, for example, to interact with instructors (B. A. Carter, M. M. Chow, personal communications, Fall 2016).

Soft, Applied, Life Disciplines

This mostly anecdotal evidence about school practices at the study location may help explain some of the participatory differences reflected in the results. The literature however, supports broader, often contradictory, disciplinary differences in course delivery, student participation, and learner achievement. Biglan’s (1973) categorization of disciplines in higher education into hard or soft, pure or applied, life or non-life, is still commonly used in research related to disciplinary differences. Based on Biglan’s (1973) categorization of disciplines, courses included in this study generally fall into the same soft and applied categories. A few of the business courses/programs, accounting and finance, for example, would fall into the non-life category, but the majority of the programs included in this study fall into the life category. The school groupings used in this study are only moderately aligned with the disciplines of education, business, and leadership. This grouping mechanism and the deidentification of the courses prevented the researcher from making more finite comparisons by discipline, such as accounting, research, management, and so on.

Wittek and Habib (2013) found differences in approaches to teaching and key activities in graduate school disciplines falling into the categories of hard and soft or pure and applied. In their study, Wittek and Habib (2013) found that math courses followed a more traditional (lecture-based) approach to teaching, whereas the education courses had a sociocultural approach. Further analysis by program or individual course subject may bring to light slightly different results, but overall, as suggested above, very few courses in this study would fall into a different category (Biglan, 1973; City University of Seattle, 2016).

Due to the similarity of disciplines included in this study, and based upon existing methods of categorization, it is more likely that the observed differences reflect unknown differences in course design and facilitation than participatory differences. Again, this study assumed similar course structure, tools for interaction, and facilitation requirements amongst the courses included in the analyses. Further analyses would need to confirm these assumptions, perhaps through course observation, to eliminate any potential impact of differences in course design and facilitation on the results of data analyses.

Recommendations for Future Research

This study benefited from a highly standardized approach to course design and facilitation. This standardization allowed the researcher to focus on specific forms of instructor participation within the LMS. In fact, as referenced above, in the School of Management, instructors were evaluated using a rubric that specified the minimum number of announcements and discussion board responses to students (see rubric, Appendix D). A similar rubric was used by the School of Applied Leadership. The researcher also limited the scope of participation to specific LMS tools and functionality required by the study location. That said, shortly after the data for this study were collected, the institution began an initiative to diversify the types of course work and activities designed into online courses in an effort to incorporate more authentic learning tasks. Some of these new designs incorporated functionality beyond that available within the LMS, such as publisher learning systems with interactive content and adaptive assessments. One school began requiring synchronous seminars a few times per term that took place within a stand-alone web conferencing tool. Future research should consider additional participatory applications within the LMS as well as external applications and/or tools. Email, for example, is another form of participation not included in this study, but believed to be used extensively by some instructors, particularly in the School of Education at the study location, for learner-to-instructor interactions.

Learner-to-learner interactions through group tools or otherwise were also beyond the scope of this study. However, as previously mentioned, graduate students have been found to place greater value on discussion board interactions with peers (Gering et al., 2018). Future research should incorporate learner-to-learner participatory tools and activities in order to make comparisons between learner-learner and learner-instructor interaction and student participation and achievement. Again, many studies have correlated learner-to-learner interaction and student satisfaction (Kuo et al., 2013; Moore, 1989), but few studies examine the impact those interactions have on students' overall participation and academic achievement in an online course.

Of particular value to the existing literature is the use of LMS log data to quantify participation by instructors and students in online courses and use the resulting data to analyze quantitatively the relationship between specific actions by the two user groups. Here again, the log data included in this study were limited in scope, in large part due to the vast amount of potential data available within the logs. LMS log data are seeing increasingly wider use in higher education (Gašević et al., 2016), but the field is still relatively new. Although LMS data are of great interest, few institutions are in a position to put the information available into action through dashboards or other means of informing instructional practices (Attaran, Stark, & Stotler, 2018). Future research should analyze any number of the vast data points recorded for use as proxy for participation. Such research would help the field identify valuable data from less useful or potentially unreliable logs. Furthermore, individual components of participation from this study, such as time in the course, course clicks, or course access should be examined as they relate to a multi-factor representation of learner achievement rather than simply traditional grades.

The log data in this study were presented in aggregate; meaning the forms of participation included in the study were represented by one number per student variable. This approach, while allowing for quick quantitative comparison, did not allow the researcher to examine changes over time. For example, this study did not indicate whether student participation started out high and declined or increased throughout the course, perhaps as a result of increasing instructor participation. Future research would benefit from a more time-based analysis of student and instructor participation within online courses.

Gašević et al. (2016) rightfully caution institutions against blanket use of LMS logs without thorough understanding of how online learning environments are being designed and utilized. While pure quantitative data can point to practices (tools, frequencies, etc.) that may impact the student experience, qualitative data related to instruction as well as the quality of course design have the potential to provide more meaningful information. Gašević et al. (2016) state:

> Findings derived from more granular course-specific models can provide instructors with better insight into the factors that affect the academic success of students, so that the findings can be 1) interpreted with respect to instructional conditions, and 2) directly used to improve teaching practice. (p. 82)

Such a follow up study to the research presented in this paper might show that frequent communication is important at first, but only those communications that further understanding or offer encouragement foster sustained participation.

A similar qualitative approach could be used to evaluate disciplinary differences in course design, online environment use, and facilitation. This study assumed online courses were designed and facilitated in a similar fashion due to institutional policy and procedures. However, as discussed previously, research has found significant differences between disciplines in their approach to teaching and learning (Wittek & Habib, 2013). During this study, the researcher heard anecdotal reports of programs ignoring institutional policies related to course design and facilitation. Without a qualitative review of the online courses included in this study, the ability to reliably compare course participation, using the same mechanisms, was limited.

Finally, this study tangentially discussed the replacement of instructors with technology in adaptive or MOOC type learning environments, where instructor interactions, such as feedback and direct instruction, are automated and/or recorded. Future researchers might explore an experimental approach to evaluating instructor participation in which one group of students might have a live instructor who provides more individualized instruction and feedback, while another group receives programmed, automated responses. Such a study would incorporate the information presented in this research, which aligns with the existing literature related to the importance of instructor presence and take it one step further in addressing whether the value added by instructors could, in some cases, be replaced by design and automation.

Conclusion

The foundational literature on best practice in online teaching and learning overwhelmingly supports the importance of teaching presence to learner success in online courses (Anderson et al., 2001; Cobb, 2009; Joo et al., 2011; Ladyshewsky, 2013; Macfadyen & Dawson, 2010; Sheridan & Kelly, 2010). Even so, one wonders if the literature and current practices are keeping pace with developments in technology. Technology has changed how we work, play, and interact with others. It is not hard to imagine that technology has also changed expectations around learning and, to some extent, how we learn (Richtel, 2012). In the shadow of such rapid change, it could be dangerous to assume that existing frameworks and categorizations apply in this new landscape. Nevertheless, new research must begin where others have left off, as it is equally perilous to negate decades of practice and research for the next fad or unverified new technology. This would seem especially true when researching the preparation of our communities and workforce of tomorrow. If this research is evidence of anything, it is that there is so much more to learn, in great part due to the same technologies fueling these changes.

Richardson et al. (2015) assert that in today's online courses, instructor social presence, the "more observable instructional behaviors ... manifested in the 'live' part of the course" (p. 259), stands apart from the design and organization categories of the CoI's teaching presence (Anderson et al., 2001). This is because instructors are more frequently removed from the design of an online course and act more as course facilitators (Richardson et al., 2015). This potentially dilutes the existing definitions of teaching presence on which this study was grounded. It is for this reason and the potential for further fragmentation of the instructor role (Bryant, 2016; Johnson et al., 2015) that this study looked exclusively at forms of "live" (Richardson et al., 2015, p. 259) teaching presence. The results indicate a significant relationship between instructor participation and student participation, but not to student achievement.

This research study adds to the existing literature supporting the importance of teaching presence and learner-to-instructor interaction to student participation in online courses. It also supports the importance of student participation to their academic success in an online course. Furthermore, it adds to the burgeoning literature on the use of LMS log data to gain insights into the teaching and learning relationship online. Specifically, this study uses log data to quantify learner participation and learner-instructor interactions falling into the CoI's teaching presence categories of direct instruction and facilitation of discourse. While not directly actionable in terms of teaching practice or course design, the results suggest that observable instructor participation plays a part in the participation of learners in online graduate courses and that learner participation has a role to play in academic achievement. More research applying LMS log files to instructor and learner activities and results in the online environment (particularly at a level allowing for evaluation on a course by course basis) is needed before traditional forms of teaching-presence in online courses can be proven essential or should be modified significantly.

In short, this study represents a small part of all that is left to research and learn. There is much more to examine from a countless number of angles in a field that continues to evolve and react at an increasing speed to the changing socioeconomic landscape. As researchers and, in many cases, educators, we owe it to our students, our colleagues, and our own profession to continue to identify research based effective practices, through our own research or that of others, in order to maximize learning in our classrooms, physical or virtual.

REFERENCES

Adamopoulos, P. (2013). *What makes a great MOOC? An interdisciplinary analysis of online course student retention.* Paper presented at the 34th International Conference on Information Systems, Milan.

Agudo-Peregrina, Á. F., Iglesias-Pradas, S., Conde-González, M. Á., & Hernández-García, Á. (2014). Can we predict success from log data in VLEs? Classification of interactions for learning analytics and their relation with performance in VLE-supported F2F and online learning. *Computers in Human Behavior, 31*, 542-550. doi:http://dx.doi.org/10.1016/j.chb.2013.05.031

Akyol, Z., & Garrison, D. R. (2008). The development of a community of inquiry over time in an online course: Understanding the progression and integration of social, cognitive and teaching presence. *Journal of Asynchronous Learning Networks, 12*(3), 3-22.

Allen, I. E., & Seaman, J. (2015). Grade level: Tracking online education in the United States. *Babson College Survey Research Group*.

Allen, I. E., & Seaman, J. (2016). Online report card: Tracking online education in the United States. Retrieved from http://onlinelearningsurvey.com/reports/onlinereportcard.pdf

Allen, J. (2005). Grades as Valid Measures of Academic Achievement of Classroom Learning. *The Clearing House: A Journal of Educational Strategies, Issues and Ideas, 78*(5), 218–223. doi:10.3200/TCHS.78.5.218-223

Anderson, T., Rourke, L., Garrison, D. R., & Archer, W. (2001). Assessing teaching presence in a computer conference context. *Journal of the Asynchronous Learning Network, 5*(2).

Arjomandi, A., Seufert, J., O'Brien, M., & Anwar, S. (2018). Active Teaching Strategies and Student Engagement: A Comparison of Traditional and Non-Traditional Business Students. *e-Journal of Business Education and Scholarship of Teaching, 12*(2), 120-140.

Artino, A., & Stephens, J. (2009). Academic motivation and self-regulation: A comparative analysis of undergraduate and graduate students learning online. *The Internet and Higher Education, 12*(3), 146-151.

Attaran, M., Stark, J., & Stotler, D. (2018). Opportunities and challenges for big data analytics in US higher education: A conceptual model for implementation. *Industry and Higher Education, 32*(3), 169-182.

Bair, D., & Bair, M. (2011). Paradoxes of online teaching. *International Journal for Scholarship of Teaching and Learning, 5*(2), 1-15.

Baker, R., & Siemans, G. (2014). Educational data mining and learning analytics. In R. K. Sawyer (Ed.), *Cambridge handbook of the learning sciences*. Cambridge, UK: Cambridge University Press.

Bandura, A. (1986). *Social foundations of thought and action: A social cognitive theory*. Englewood Cliffs, NJ: PrenticeHall.

Bandura, A. (1994). Self-efficacy. In V. S. Ramachaudran (Ed.), *Encyclopedia of human behavior* (Vol. 4). New York: Academic Press.

Bandura, A. (2006). On Integrating Social Cognitive and Social Diffusion Theories. In A. Singhal & J. Dearing (Eds.), *Communications of Innovations: A Journey with Ev Rogers* (pp. 111-135). Beverley HIlls: Sage Publications.

Bandura, A., & Locke, E. A. (2003). Negative self-efficacy and goal effects revision. *Journal of Applied Psychology, 88*(87-99).

Bates, A. T. (2015). *Teaching in a digital age: Guidelines for designing teaching and learning*.

Battalio, J. (2007). Interaction online: A reevaluation. *Quarterly Review of Distance Education, 8*(4), 339-352.

Batts, D., Pagliari, L., Mallett, W., & McFadden, C. (2010). Training for faculty who teach online. *Community College Enterprise, 16*(2), 21-31.

Beer, C., Clark, K., & Jones, D. (2010). *Indicators of engagement*. Paper presented at the ascilite: Curriculum, technology & transformation for an unknown future, Sydney. http://www.ascilite.org/conferences/sydney10/proceedings.htm

Bell, B. S., & Federman, J. E. (2013). E-learning in postsecondary education. *The Future of Children, 23*(1), 165-185.

Benshoff, J., Cashwell, C., & Rowell, P. (2015). Graduate Students on Campus: Needs and Implications for College Counselors. *Journal of College Counseling, 18*(1), 82-94.

Berg, G. A. (2002). *Why distance learning?: Higher education administrative practices.* Westport, CT: Praeger Publishers.

Berrett, D. (2012). Grades and Tests May Miss What Matters Most in Learning. , n/a. Retrieved from. *The Chronicle of Higher Education, n/a*.

Biglan, A. (1973). Relationships between subject matter characteristics and the structure and output of university departments. *Journal of Applied Psychology, 57*(1204-1213).

Blackboard Inc. (2016). Blackboard Help: Announcements.   Retrieved from https://en-us.help.blackboard.com/Learn/9.1_2014_04/Instructor/060_Communication/030_Announcements

Brookhart, S., Guskey, T., Bowers, A., McMillan, J., Smith, J., Smith, L., . . . Welsh, M. E. (2016). A Century of Grading Research. *Review of Educational Research, 86*(4), 803–848. doi:10.3102/0034654316672069

Bryant, G. (2016). Learning to Adapt 2.0: The Evolution of Adaptive Learning in Higher Education. Retrieved from Tyton Partners website: http://tytonpartners.com/library/learning-to-adapt-2-0-the-evolution-of-adaptive-learning-in-higher-education/

Calafiore, P., & Damianov, D. S. (2011). The effect of time spent online on student achievement in online economics and finance courses. *The Journal of Economic Education, 42*(3), 209-223.

Calsolaro Smulsky, N. (2012). *Measuring Student-Faculty Interaction for Nontraditional College Students: A Comparison of Data Collection Tools.* Online Submission.

Campbell, D. E. (2014). The Influence of Teacher Immediacy Behaviors on Student Performance in an Online Course (and the Problem of Method Variance). *Teaching of Psychology, 41*(2), 163-166.

Cavanaugh, J. (2005). Teaching online-A time comparison. *Online Journal of Distance Learning Administration, 8*(1).

Cheng, C. K., Paré, D. E., Collimore, L. M., & Joordens, S. (2011). Assessing the effectiveness of a voluntary online discussion forum on improving students' course performance. *Computers & Education, 56*(1), 253-261.

Chickering, A. W., & Gamson, Z. F. (1999). Development & adaptations of the seven principles of good practice in undergraduate education. *New directions for Teaching and Learning, 1999*(8), 75-81. doi:10.1002/tl.8006

Chyung, S. Y. (2007). Age and gender difference in online behavior, self-efficacy, and academic performance. *Quarterly Review of Distance Education*, *8*(3), 213–222.

City University of Seattle. (2013). *Course Delivery Modes and the Learning Management System (LMS) Policy*. Seattle: Author.

City University of Seattle. (2016). City University of Seattle Catalog 2016 - 2017. Retrieved from https://www.cityu.edu/catalog/

City University of Seattle. (2019). Washington School of Languages. Retrieved from https://www.cityu.edu/wal/

Cobb, S. C. (2009). Social presence and online learning: A current view from a research perspective. *Journal of interactive Online Learning*, *8*(3).

Competency-based Education Network. (2016). Competency-based education network. Retrieved from http://www.cbenetwork.org/competency-based-education/

Council of Regional Accrediting Commissions. (2011). *Interregional guidelines for the evaluation of distance education programs (online learning)*

Dennen, V. P., Aubteen Darabi, A., & Smith, L. J. (2007). Instructor–learner interaction in online courses: The relative perceived importance of particular instructor actions on performance and satisfaction. *Distance Education, 28*(1), 65-79.

Dewey, J. (1938). *Experience and education*. New York, N.Y: Touchstone.

Dewey, J. (1959). My pedagogic creed. In J. Dewey (Ed.), *Dewey on education*. New York: Bureau of Publications, Teachers College, Columbia University.

Enightoola, K., Fraser, S., & Brunton, T. (2014). Exploring the Community of Inquiry model: Students' attitudes towards e-learning. *The Caribbean Teaching Scholar, 4*(2), 81–98.

Fain, P. (2014). For-profits lead the way as adaptive learning becomes more popular. *Inside Higher Ed*. Retrieved from Inside Higher Ed website: https://www.insidehighered.com/news/2014/06/13/profits-lead-way-adaptive-learning-becomes-more-popular

Fain, P. (2015). Defining Competency. *Inside Higher Ed: Teaching and Learning*. Retrieved from Inside Higher Ed website: https://www.insidehighered.com/news/2015/06/17/new-letters-us-and-accreditors-provide-framework-approval-competency-based-degrees

Falakmasir, M. H., & Habibi, J. (2010). *Using Educational Data Mining Methods to Study the Impact of Virtual Classroom in E-Learning*. Paper presented at the Educational Data Mining, Pittsburg, PA.

Fedynich, L. V. (2014). Teaching beyond the classroom walls: The pros and cons of cyber learning. *Journal of Instructional Pedagogies, 13*(1).

Field, A. (2009). *Discovering Statistics Using SPSS* (3rd ed.). Thousand Oaks, CA: SAGE Publications Ltd.

Francois, E. (2014). Motivational orientations of non‐traditional adult students to enroll in a degree‐seeking program. *New Horizons in Adult Education and Human Resource Development*, *26*(2), 19-35.

Garrison, D. R., & Akyol, Z. (2013). The community of inquiry theoretical framework. In M. G. Moore (Ed.), *Handbook of distance education* (3 ed., pp. 104-120). New York, NY: Routledge.

Garrison, D. R., Anderson, T., & Archer, W. (2000). Critical inquiry in a text-based environment: Computer conferencing in higher education. *The Internet and Higher Education*, *2*(2-3), 87-105.

Garrison, D. R., Anderson, T., & Archer, W. (2010). The first decade of the community of inquiry framework: A retrospective. *The Internet and Higher Education, 13*(1), 5-9.

Garrison, D. R., & Cleveland-Innes, M. (2005). Facilitating cognitive presence in online learning: Iteraction is not enough. *The American Journal of Distance Education, 19*(3), 133-148.

Gašević, D., Dawson, S., Rogers, T., & Gasevic, D. (2016). Learning analytics should not promote one size fits all: The effects of instructional conditions in predicting academic success. *The Internet and Higher Education, 28*(C), 68-84.

Gašević, D., Dawson, S., & Siemens, G. (2015). Let's not forget: Learning analytics are about learning. *TechTrends, 59*(1), 64-71.

Gering, C., Sheppard, D., Adams, B., Renes, S., & Morotti, A. (2018). Strengths-based analysis of student success in online courses. *Online Learning, 22*(3), 55-85.

Giossos, Y., Koutsouba, M., Lionarakis, A., & Skavantzos, K. (2009). Reconsidering Moore's Transactional Distance Theory. *European Journal of Open, Distance and E-Learning, 2*.

Gliner, J. A., Morgan, G. A., & Leech, N. L. (2009). *Research Methods in Applied Settings: An Integrated Approach to Design and Analysis* (2nd ed.). New york City, NY: Routledge.

Gopalan, C. (2016). The impact of rapid change in educational technology on teaching in higher education. *Journal of the Human Anatomy and Physiology Society 20*(4), 85-90. doi:10.21692/haps.2016.036

Gunawardena, C. N., & Zittle, F. J. (1997). Social presence as a predictor of satisfaction with a computer-mediated conferencing environment. *American Journal of Distance Education, 11*(8-26).

Harden, N. (2012). The end of the university as we know it. *The American Interest*. Retrieved from http://www.the-american-interest.com/articles/2012/12/11/the-end-of-the-university-as-we-know-it/#sthash.uv46xn1y.dpuf

He, W. (2013). Examining students' online interaction in a live video streaming environment using data mining and text mining. *Computers in Human Behavior, 29*(1), 90-102.

Henrie, C. R., Halverson, L. R., & Graham, C. R. (2015). Measuring student engagement in technology-mediated learning: A review. *Computers & Education, 90*, 36-53. doi:http://dx.doi.org/10.1016/j.compedu.2015.09.005

Hernández-García, Á., González-González, I., Jiménez-Zarco, A. I., & Chaparro-Peláez, J. (2015). Applying social learning analytics to message boards in online distance learning: A case study. *Computers in Human Behavior, 47*, 68-80.

Heuer, B. P., & King, K. P. (2004). Leading the band: The role of the instructor in online learning for educators. *The Journal of Interactive Online Learning, 3*(1), 1-11.

Hew, K. F., & Cheung, W. S. (2014). Students' and instructors' use of massive open online courses (MOOCs): Motivations and challenges. *Educational Research Review, 12*(6), 45-58. doi:10.1016/j.edurev.2014.05.001

Hillman, D. C. A., Willis, D. J., & Gunawardena, C. N. (1994). Learner-interface interaction in distance education: An extension of contemporary models and strategies for practitioners. *The American Journal of Distance Education, 8*(2), 30-42.

Hrastinski, S. (2008). What is online learner participation? A literature review. *Computers & Education, 51*(4), 1755-1765. doi:http://dx.doi.org/10.1016/j.compedu.2008.05.005

Hrastinski, S. (2009). A theory of online learning as online participation. *Computers & Education, 52*(1), 78-82. doi:http://dx.doi.org/10.1016/j.compedu.2008.06.009

International Educational Data Mining Society. (n.d.). Educational Data Mining. Retrieved from http://www.educationaldatamining.org/

Jaldemark, J., Lindberg, J. O., & Olofsson, A. D. (2005). *Learning with others as learning by myself*. Paper presented at the The Challenge of Integrating ICT in Teacher Education. The Need for Dialogue, Change and Innovation.

Javadi, E., & Rajandran, T. (2013). *Traces of Students' Performances in Online Activity Logs.* Paper presented at the The Midwest Association for Information.

Johnson, D., & Samora, D. (2016). The Potential Transformation Of Higher Education Through Computer-Based Adaptive Learning Systems. *Global Education Journal, 2016*(1), 1-17.

Johnson, L., Adams Becker, S., Estrada, V., & Freeman, A. (2015). *NMC Horizon Report: 2015 Higher Education Edition*. Retrieved from Austin, TX: http://cdn.nmc.org/media/2015-nmc-horizon-report-HE-EN.pdf

Joksimović, S., Gašević, D., Loughin, T. M., Kovanović, V., & Hatala, M. (2015). Learning at distance: Effects of interaction traces on academic achievement. *Computers & Education, 87*(204-217).

Jones, S., & Johnson-Yale, C. (2005). Professors online: The Internet's impact on college faculty. *First Monday, 10*(9).

Joo, Y. J., Lim, K. Y., & Kim, E. K. (2011). Online university students' satisfaction and persistence: Examining perceived level of presence, usefulness and ease of use as predictors in a structural model. *Computers & Education, 57*(2), 1654-1664. doi:http://dx.doi.org/10.1016/j.compedu.2011.02.008

Kahneman, D. (2011). *Thinking Fast and Slow*. New York City, NY: Farrar, Straus and Giroux.

Kim, D., Park, Y., Yoon, M., & Jo, I. H. (2016). Toward evidence-based learning analytics: Using proxy variables to improve asynchronous online discussion environments. *The Internet and Higher Education, 30*, 30-43.

Kim, J., Kwon, Y., & Cho, D. (2011). Investigating factors that influence social presence and learning outcomes in distance higher education. *Computers & Education, 57*(2), 1512-1520. doi:http://dx.doi.org/10.1016/j.compedu.2011.02.005

King, E. J., & Tanner, E. J. (2015). Quality of Asynchronous Discussions: A Case Study of Professor Impact. *American International Journal of Comtempary Research, 5*(5), 35-42.

Kirp, D. L. (2013). Tech mania goes to college: Are MOOCs the utopia of affordable education, or just the latest fad? *The Nation*.

Klafter, C. (2019). Good Grieve! America's Grade Inflation Culture. *Academic Questions,, 32*(3), 328-333. doi:https://doi.org/10.1007/s12129-019-09810-8

Komarraju, M., & Nadler, D. (2013). Self-efficacy and academic achievement: Why do implicit beliefs, goals, and effort regulation matter? *Learning and Individual Differences, 25*, 67-72.

Koohang, A. (2012). Active learning in e-learning: advancing a systemic model. *Issues in Information Systems, 13*(1), 68-76.

Kuo, Y., Walker, A. E., Belland, B., & Schroder, K. (2013). A predictive study of student satisfaction in online education programs. *The International Review Of Research In Open And Distributed Learning, 14*(1), 16-39.

Kuo, Y., Walker, A. E., Schroder, K. E. E., & Belland, B. R. (2014). Interaction, Internet self-efficacy, and self-regulated learning as predictors of student satisfaction in online education courses. *The Internet and Higher Education, 20*, 35-50. doi:http://dx.doi.org/10.1016/j.iheduc.2013.10.001

Ladyshewsky, R. K. (2013). Instructor presence in online courses and student satisfaction. *International Journal for the Scholarship of Teaching and Learning, 7*(1), 13.

Lemoine, P. A., Seneca, S., & Richardson, M. D. (2019). Resilience for faculty development in global higher education *Handbook of Research on Faculty Development for Digital Teaching and Learning* (pp. 481-504): IGI Global.

Li, Q., & Akins, M. (2005). Sixteen myths about online teaching and learning in higher education: Don't believe everything you hear. *TechTrends, 49*(4), 51-60.

Lockyer, L., Heathcote, E., & Dawson, S. (2013). Informing pedagogical action: Aligning learning analytics with learning design. *American Behavioral Scientist, 57*(10), 1439–1459.

Lund Research Ltd. (2018). *Laerd Statistics* Retrieved from https://statistics.laerd.com/aboutus.php

Ma, J., Han, X., Yang, J., & Cheng, J. (2015). Examining the necessary condition for engagement in an online learning environment based on learning analytics approach: The role of the instructor. *The Internet and Higher Education, 24*, 26-34. doi:http://dx.doi.org/10.1016/j.iheduc.2014.09.005

Macfadyen, L. P., & Dawson, S. (2010). Mining LMS data to develop an "early warning system" for educators: A proof of concept. *Computers & Education, 54*(2), 588-599. doi:http://dx.doi.org/10.1016/j.compedu.2009.09.008

Mandernach, B. J., Gonzales, R. M., & Garrett, A. L. (2006). An examination of online instructor presence via threaded discussion participation. *Journal of Online Learning and Teaching, 2*(4), 248-260.

Marini, J., Shaw, E., Young, L., & Ewing, M. (2018). *Getting to Know Your Criterion: Examining College Course Grades and GPAs over Time*. Retrieved from New York, NY:

McFarland, J., Hussar, B., Zhang, J., Wang, X., Wang, K., Hein, S., . . . Barmer, A. (2019). *The Condition of Education 2019* (NCES 2019-144). Retrieved from https://nces.ed.gov/pubs2019/2019144.pdf

Microcredentials Research Group. (2016). Microcredentials Research Group: How do people use microcredentials, badges, and other formal markers of online reputation? .   Retrieved from http://altcred.org/about/

Mohamad, S. K., & Tasir, Z. (2013). Educational Data Mining: A Review. *Procedia - Social and Behavioral Sciences, 97*, 320-324. doi:http://dx.doi.org/10.1016/j.sbspro.2013.10.240

Moore, J. L., Dickson-Deane, C., & Galyen, K. (2011). e-Learning, online learning, and distance learning environments: Are they the same? *The Internet and Higher Education, 14*(2), 129-135. doi:10.1016/j.iheduc.2010.10.001

Moore, M. G. (1989). Three types of interactions. *The American Journal of Distance Education, 3*(2), 1-6.

Moore, M. G. (1993). Theory of transactional distance. In D. Keegan (Ed.), *Theoretical principles of distance education* (pp. 22-38). New York, NY: Routledge.

Moore, M. G., & Kearsley, G. (2011). *Distance education: A systems view of online learning. Cengage Learning.* (3 ed.). Belmont, CA: Wadsworth, Cengage Learning.

Morris, L. V., Finnegan, C., & Wu, S. (2005). Tracking student behavior, persistence, and achievement in online courses. *The Internet and Higher Education, 8*(3), 221-231. doi:http://dx.doi.org/10.1016/j.iheduc.2005.06.009

Nagel, L., & Kotzé, T. G. (2010). Supersizing e-learning: What a CoI survey reveals about teaching presence in a large online class. *The Internet and Higher Education, 13*(1–2), 45-51. doi:http://dx.doi.org/10.1016/j.iheduc.2009.12.001

National Center for Education Statistics. (May 2016). The condition of education: Characteristics of postsecondary students. Retrieved from http://nces.ed.gov/programs/coe/indicator_csb.asp

National Center for Education Statistics. IPEDS: About IPEDS. Retrieved from http://nces.ed.gov/ipeds/Home/AboutIPEDS

Office of Human Research Protections. (2009). Code of federal regulations: Title 45 public welfare Department of Health and Human Services Part 46 protection of human subjects Retrieved from https://www.hhs.gov/ohrp/regulations-and-policy/regulations/45-cfr-46/index.html#46.115

Oracle Corporation. (2017). MySQL 5.7 Referance Manual: What is MySQL. Retrieved from https://dev.mysql.com/doc/refman/5.7/en/what-is-mysql.html

Papamitsiou, Z., & Economides, A. (2014). Learning Analytics and Educational Data Mining in Practice: A Systematic Literature Review of Empirical Evidence. *Journal of Educational Technology & Society, 17*(4), 49-64.

Paris, D. (2013). The Last Artisans? Traditional and Future Faculty Roles. *Peer Review, 15*(3), 17-20.

Parry, M., Field, K., & Supiano, B. (2013). The Gates effect. *The Chronicle of Higher Education*. Retrieved from http://chronicle.com/article/The-Gates-Effect/140323/.

Patten, M. L. (2012). *Understanding Research Methods: An Overview of the Essentials* (8th ed.). Glendale, CA: Pyrczak Publishing.

Peña-Ayala, A. (2014). Educational data mining: A survey and a data mining-based analysis of recent works. *Expert Systems with Applications, 41*(4, Part 1), 1432-1462. doi:http://dx.doi.org/10.1016/j.eswa.2013.08.042

Picciano, A. G. (2002). Beyond student perceptions: Issues of interaction, presence, and performance in an online course. *Journal of Asynchronous Learning Networks, 6*(1), 21-40.

Pittman, V. V. (2013). University correspondence study: A revised historiogrphic perspective. In M. G. Moore (Ed.), *Handbook of distance education. Routledge.* (3 ed., pp. 21-37). New York, NY: Routledge.

Preisman, K. A. (2014). Teaching presence in online education: From the instructor's point of view. *Online Learning, 18*(3).

Psaromiligkos, Y., Orfanidou, M., Kytagias, C., & Zafiri, E. (2011). Mining log data for the analysis of learners' behaviour in web-based learning management systems. *Operational Research, 11*(2), 187-200. doi:10.1007/s12351-008-0032-4

Rao, K. (2012). *Universal design for online courses: Addressing the needs of non-traditional learners*. Paper presented at the International Conference on Technology Enhanced Education (ICTEE), Kerala, India.

Ravenna, G., Foster, C., & Bishop, C. (2012). Increasing Student Interaction Online: A Review of the Literature in Teacher Education Programs. *Journal of Technology and Teacher Education, 20*(2), 177-203.

Richardson, J. C., Koehler, A. A., Besser, E. D., Caskurlu, S., Lim, J., & Mueller, C. M. (2015). Conceptualizing and investigating instructor presence in online learning environments. *The International Review Of Research In Open And Distributed Learning, 16*(3), 256–297.

Richtel, M. (2012). Technology changing how students learn, teachers say. *The New York Times*. Retrieved from https://www.nytimes.com/2012/11/01/education/technology-is-changing-how-students-learn-teachers-say.html?_r=0

Romero, C., López, M., Luna, J., & Ventura, S. (2013). Predicting students' final performance from participation in on-line discussion forums. *Computers & Education, 68*, 458-472. doi:http://dx.doi.org/10.1016/j.compedu.2013.06.009

Rumble, G. (2004). *Papers and debates on the economics and costs of distance and online learning* (Vol. 7). Oldenburg, Germany: Bibliotheks- und Informationssystem der Universität Oldenburg.

Schulte, M. (2010). Faculty perceptions of technology distance education transactions: Qualitative outcomes to inform teaching practices. *Journal of Educators Online, 7*(2), 34.

Schunk, D. H. (2012). *Learning theories: An educational perspective* (6th ed.). Boston, MA: Pearson.

Schwab, K., Moseley, B., & Dustin, D. (2018). Grading Grades as a Measure of Student Learning. *SCHOLE: A Journal of Leisure Studies and Recreation Education, 33*(2), 87-95. doi:10.1080/1937156X.2018.1513276

Seaman, E., Allen, I. E., & Seaman, J. (2018). *Grade increase: Tracking distance education in the United States*. Retrieved from https://www.onlinelearningsurvey.com/highered.html

Serhan, D. (2010). Online learning: through their eyes.(Report). *International Journal of Instructional Media, 37*(1).

Shaw, R. S. (2012). A study of the relationships among learning styles, participation types, and performance in programming language learning supported by online forums. *Computers & Education, 58*(1), 111-120.

Shea, P. (2006). A study of students' sense of learning community in online environments. *Journal of Asynchronous Learning Networks, 10*(1), 35-44.

Shea, P., & Bidjerano, T. (2009). Community of Inquiry as a theoretical framework to foster "epistemic engagement" and "cognitive presence" in online education. *Journal of Asynchronous Learning Networks, 52*(3), 543-553.

Shea, P., & Bidjerano, T. (2010). Learning presence: Towards a theory of self-efficacy, self-regulation, and the development of a communities of inquiry in online and blended learning environments. *Computers & Education, 55*(4), 1721-1731. doi:https://doi.org/10.1016/j.compedu.2010.07.017

Shea, P., Pickett, A. M., & Pelz, W. E. (2003). A follow up investigation of "teaching presence" in the SUNY Learning Network. *Journal of Asynchronous Learning Networks, 7*(2), 61-80.

Sheridan, K., & Kelly, M. A. (2010). The indicators of instructor presence that are important to students in online courses. *Journal of Online Learning and Teaching, 6*(4), 767-779.

Siemans, G., & Gašević, D. (2012). Special issue on learning and knowledge analytics. *Educational Technology & Society, 15*(3), 1-163.

Smith, V. C., Lange, A., & Huston, D. R. (2012). Predictive Modeling to Forecast Student Outcomes and Drive Effective Interventions in Online Community College Courses. *Journal of Asynchronous Learning Networks, 16*(3), 51-61.

Spector, J. M. (2005). Time demands in online instruction. *Distance Education, 26*(1), 5-27. doi:10.1080/01587910500081251J

Swan, K. P. (2001). Virtual interaction: Design factors affecting student satisfaction and preceived learning in asynchronous online courses. *Distance Education, 22*(2), 306-331. doi:10.1080/0158791010220208

Swan, K. P., Richardson, J. C., Ice, P., Garrison, D. R., Cleveland-Innes, M., & Arbaugh, J. B. (2008). Validating a measurement tool of presence in online communitiesof inquiry. *ementor, 2*(24).

Tirrell, T., & Quick, D. (2012). Chickering's seven principles of good practice: Student attrition in community college online courses. *Community College Journal of Research and Practice, 36*(8), 580-590.

Tomkin, J., & Charlevoix, D. (2014). *Do professors matter?: using an a/b test to evaluate the impact of instructor involvement on MOOC student outcomes.* Paper presented at the ACM Conference on Learning @ Scale, Atlanta, GA

Trolian, T., Jach, E., Hanson, J., & Pascarella, E. (2016). Influencing Academic Motivation: The Effects of Student-Faculty Interaction. *Journal of College Student Development, 57*(7), 810-826.

Tucker, J., Au, A., & Neely, P. (2015). *A Comparison of Traditional vs. Competency-based Education Faculty Roles*. Paper presented at the Society for Information Technology &

Teacher Education International Conference 2015, Las Vegas, NV, United States. https://www.learntechlib.org/p/150049

van Leeuwen, A., Janssen, J., Erkens, G., & Brekelmans, M. (2015). Teacher regulation of cognitive activities during student collaboration: Effects of learning analytics. *Computers & Education, 90, 80-94., 90*, 80-94.

Vella, E. J., Turesky, E. F., & Hebert, J. (2016). Predictors of academic success in web-based courses: age, GPA, and instruction mode. *Quality Assurance in Education, 24*(4), 586-600.

Vygotsky, L. S. (1978). *Mind in society: The development of higher psychological processes*. Cambridge, MA: Harvard University Press.

Vygotsky, L. S. (1986). *Thought and language - Revised edition* (A. Kozulin Ed.). Boston, MA: MIT Press.

Wang, J., & Antonenko, P. (2017). Instructor presence in instructional video: Effects on visual attention, recall, and perceived learning. . *Computers in Human Behavior, 71*, 79-89.

Wang, J., Doll, W. J., Deng, X., Park, K., & Yang, M. G. M. (2013). The impact of faculty perceived reconfigurability of learning management systems on effective teaching practices. *Computers & Education, 61*(146-157). doi:10.1016/j.compedu.2012.09.005

Wei, H. C., Peng, H., & Chou, C. (2015). Can more interactivity improve learning achievement in an online course? Effects of college students' perception and actual use of a course-management system on their learning achievement. *Computers & Education, 83*, 10-21.

WhatIs.com. (May 2011). Definition: Discussion board (discussion group, message board, online forum). Retrieved from http://whatis.techtarget.com/definition/discussion-board-discussion-group-message-board-online-forum

Wise, A. F., Speer, J., Marbouti, F., & Hsiao, Y. T. (2013). Broadening the notion of participation in online discussions: examining patterns in learners' online listening behaviors. *Instructional Science, 41*(2), 323-343.

Wittek, L., & Habib, L. (2013). Quality teaching and learning as practice within different disciplinary discourses. *International Journal of Teaching and Learning in Higher Education, 25*(3), 275-287.

Wolf, P. D. (2006). Best practices in the training of faculty to teach online. *Journal of Computing in Higher Education, 17*(2), 47-78.

You, J. W. (2016). Identifying significant indicators using LMS data to predict course achievement in online learning. *The Internet and Higher Education, 29*, 23-30. doi:http://dx.doi.org/10.1016/j.iheduc.2015.11.003

Zimmerman, B., & Schunk, D. (2001). Theories of self-regulated learning and academic achievment: an overview and analysis. In B. Zimmerman & D. Schunk (Eds.), *Self regulated learning and academic achievement: Theoretical perspectives* (2 ed., pp. 1–36). Mahwah, NJ: Lawrence Erlbaum.

APPENDIX A

CITY UNIVERSITY OF SEATTLE IRB CERTIFICATE OF APPROVAL

www.CityU.edu

206.239.4800 [Main]
800.426.5596 [Toll-Free]
City University of Seattle
521 Wall Street, Suite 100
Seattle, WA 98121

Institutional Review Board
Certificate of Approval

IRB ID# Thornbury_Faculty041818

Principal Investigator (if faculty research):
Student Researcher:
Faculty Advisor: Erin Thornbury
Department: eLearning

Title: The relationship between instructor course participation, student participation and student performance in online courses.
Approved on: April 18, 2018
Renewal Date: April 18, 2019

- ☐ Full Board Meeting Date of IRB meeting: _______________
- X Expedited Review (US)
- ☐ Delegated Review (Can)
- ☐ Exempt (US)

CERTIFICATION

City University of Seattle has reviewed the above-named research project. The proposal was found to be acceptable on ethical grounds. The Faculty Erin Thornbury has the responsibility for any other administrative or regulatory approvals that may pertain to this research project, and for ensuring that the authorized research is carried out according to the conditions outlined in the original Ethical Review Protocol submitted for ethics review. This ***Certificate of Approval*** is valid for the above time period provided there is no change in experimental protocol, consent process, or documents.
Any significant changes to your proposed method, or your consent and recruitment procedures should be reported to the Chair of the Institutional Review Board in advance of its implementation.

ONGOING REVIEW REQUIREMENTS

In order to receive annual renewal, a status report must be submitted to the IRB Chair for Board consideration within one month of the current expiry date each year the study remains open, and upon study completion.

Brian Guthrie

Brian Guthrie Ph D, RSW, RCSW
Chair, IRB City University of Seattle

APPENDIX B

UNIVERSITY OF TENNESSEE AT CHATTANOOGA IRB LETTER OF DEFERRAL

THE UNIVERSITY OF TENNESSEE
CHATTANOOGA

Institutional Review Board
Dept 4915
615 McCallie Avenue
Chattanooga, TN 37403
Phone: (423) 425-5867
Fax: (423) 425-4052
instrb@utc.edu
http://www.utc.edu/irb

5/21/2018

Erin Noseworthy
Dr. Ted Miller

The Relationship Between Instructor Course Participation, Student Participation, and Student Performance in Online Courses (IRB ID Thornbury _Faculty 041818)

Please let this letter serve as the official authorization that The University of Tennessee at Chattanooga is deferring the research approval to the Institutional Review Board at the City University of Seattle for IRB) which approved the research protocol on April 18, 2018.

The University of Tennessee at Chattanooga complies with all state and federal regulations governing research involving human subjects and assures that these processes will be implemented for the research that is done on our campus. If you would like additional information about the Institutional Review Board at the University of Tennessee at Chattanooga please refer to our website at www.utc.edu/irb or feel free to contact me directly at Lindsay-pardue@utc.edu or via telephone at 423/425-4443.

Sincerely,

Lindsay Pardue

Lindsay Pardue
Director, Office of Research Integrity &
Research Compliance Officer
423-425-4443, Lindsay-Pardue@utc.edu

APPENDIX C

VARIABLES ANALYSIS

VARIABLES ANALYSIS

	Variable Label	**Levels of the Variable**	**Scale of Measurement**
Dependent Variables	Student course grade	0.0 - 4	Scale
	Student discussion board posts	0 or more	Scale
	Student course log-ins	0 or more	Scale
	Student clicks within the course	0 or more	Scale
	Student time in course	0 or more minutes	Scale
Independent Variables	Instructor announcements	0 or more	Scale
	Instructor discussion board posts	0 or more	Scale
Attributional Variables	Student in Course	Anonymous Identifier	Nominal
	Student gender	1 = Female 2 = Male 3 = Not Specified	Nominal
	Student credits completed (as specified on transcript)	0 or more	Scale
	Student school	1 = Washington Academy of Language 2 = Albright School of Education 3 = School of Management 4 = School of Applied Leadership	Nominal
	Student age	18-24 25-34 35-44 45-54 55-64 65+	Ordinal
	Course School	1 = Washington Academy of Language 2 = Albright School of Education 3 = School of Management 4 = School of Applied Leadership	Nominal

APPENDIX D

SCHOOL OF MANAGEMENT QUALITY CONTROL RUBRIC

QC RUBRIC				
Areas of Evaluation	Below Standard 1	Approaching Standard 2	At Standard 3	Exceeds Standard 4
Announcements	Standard welcome announcement not personalized or edited. Less than one announcement per week. Some or all announcements are hidden or not visible to students. Announcements mainly course mechanics. No meaningful content. Announcement tone and language offensive or insulting. Poor language choices in announcements. Does not provide or identify key information items.	Perfunctory welcome announcement first week. Not completely tailored to the course/instructor. At least one announcement per week. Previous weeks' announcements are hidden or not visible to students. Announcements mainly course mechanics not including a summary of previous week's discussion, a preview of coming week or addressing topics/contents that affect the whole class. Announcement tone is neutral and mechanical. Does not clearly distinguish key information items.	Edited and personalized welcome announcement first week. At least one announcement per week. All subsequent announcements are visible to students and are in chronological order Announcements for the week are more than just mechanics. They provide instructional guidance including, summary of previous week's content; preview of coming week. Announcement tone is positive and encouraging.	Announcements more than just course mechanics including multiple features such as: summary of previous week's discussion; preview of coming week; or address topics/contents that affect the whole class. Announcements have meaningful/useful content including: items related to the courses that are of interest to the students such as professional experiences related to the weekly assignments and readings. Announcements are customized and show positive personality. Some announcements incorporate multi-media links.

Areas of Evaluation	Below Standard 1	Approaching Standard 2	At Standard 3	Exceeds Standard 4
In-class Observation of Instruction (subs for DB)	Provides little or inappropriate academic/intellectual challenge. Is disorganized and inconsistent in the presentation of course content. Does not clearly communicate core concepts of the course or identify the key aspects of the material. Little or no attention given to the emotional climate among the class members. Rarely provides opportunities to ask clarifying questions or discuss feedback. Opportunities for students learning from each other are rarely apparent. No mention of peer feedback processes, group roles, or guidance on teamwork. Employs primarily one	Provides occasional academic/intellectual challenge. Mainly reiterates or points to text of assignments and syllabus. Is sometimes disorganized and inconsistent in the presentation of course content. Attention to emotional climate sometimes evident, but no explicit discussion of norms. Provides limited opportunities to ask clarifying questions. Occasionally invites students to discuss feedback. Opportunities for students learning from each other limited to discussion requirement and presentations. Employs a limited number of teaching strategies that are	Provides appropriate academic/intellectual challenge. Is organized and consistent in presenting the course content. Communicates core concepts clearly and focuses the students on key aspects of the material. Provides low-risk practice opportunities for students. Provides opportunity for student input and sharing of expertise in class/online session. Proactively reaches out to students. Makes use of the classroom, physical or electronic, to encourage students to learn from each other through idea sharing, study groups, student presentations or other appropriate methods.	Provides dynamic academic/intellectual challenge that meets learners where they are and takes them where they need to go. Is highly organized and consistent in presenting the course content. Uses multiple methods to ensure core concepts are clearly communicated and understood. Ensures students focus on key aspects of the material. Fosters trust and supports low-risk practice opportunities for students to perform according to their preferred learning style. Attempts to engage all students in the class by offering multiple ways of participating. Invites discussion of feedback.

	teaching strategy during the session. Comments often are off topic, rude, unprofessional, arrogant, or discourage further student discussions.	minimally effective for diverse learners. Rarely promotes critical thinking and collaboration.	Employs multiple pathways during the course session to engage diverse learners (watching, listening, practicing in whole-group discussion, lecture, cooperative small-group learning, performance task, other. Promotes some critical thinking and collaboration, ask pertinent questions to further discussion, encourage students, or relate professional experience.	Makes regular and extensive use of the classroom, physical or electronic to encourage students to learn from each other through idea sharing, study groups, student presentations, or other appropriate methods. Promote critical thinking and collaboration, provide expertise and guidance, share insight, ask pertinent questions to further discussion, encourage students, or relate professional experience (war stories).

Areas of Evaluation	Below Standard 1	Approaching Standard 2	At Standard 3	Exceeds Standard 4
Discussion Board/Instructor Determined Activity	Limited quantity and frequency of instructor posting reflecting a lack of involvement in the course. No responses to students' threads. Comments often are off topic, rude, unprofessional, arrogant, or discourage further student discussions. Provides no content in posts. Students obviously not engaged in the course.	Quantity and frequency of instructor posting which reflect moderate involvement in the course. Only responding to less than 50% of the students' threads. Only responding with "good posting" or "I agree with you" with no insight or thoughtfulness. Limited number meaningful posts that promote critical thinking and collaboration. Provides no content in posts. Limited evidence of student engagement. Not responding to student threads within 72 hours.	Instructor appropriately manages the Discussion Board (placing the current weeks prompt at the top of the list). Responds to 100% of SIA posts. Responds to 50% or more of the students' initial threads within the learning week Posts provide guidance and promote critical thinking and collaboration, ask pertinent questions to further discussion, encourage students, or relate professional experience. Instructor uses Discussion Board as a teaching platform. Responds to threads within 48 hours.	Quantity and frequency of instructor posting which reflect high level of involvement in the course. Responds to 100% of students' threads. Postings are almost all high quality postings that promote critical thinking and collaboration, provide expertise and guidance, share insight, ask pertinent questions to further discussion, encourage students, or relate professional experience (war stories). Postings include significant content, lengthy and detailed responses, or discussions beyond base content. Discussions include multiple media, including video, etc. Responds to threads within 24 hours.

Areas of Evaluation	Below Standard 1	Approaching Standard 2	At Standard 3	Exceeds Standard 4
Faculty Information	Instructor has not listed their name and contact information in the Faculty Information tab. Instructor has not included a profile picture. There is no instructor bio that includes: professional experience as related to the course, degrees obtained and from what institutions.	Instructor has neglected to include any of the following: • Name and contact information • Profile picture • Faculty bio	Instructor has listed their name and contact information (instructor email and phone number). Instructor has listed their response time expectations for emails (no more than 48 hours). Instructor has included a professional profile picture that is sized to scale. There is an instructor bio that includes the following: professional experience as related to the course, degrees or certificates obtained and from what institutions (and link to bio if appropriate).	

Areas of Evaluation	Below Standard 1	Approaching Standard 2	At Standard 3	Exceeds Standard 4
Grade Book	Frequent late grading of assignments. DB grades posted more than one week after the session has ended. Instructor not using inline grading rubric for DB grades. Grade book not correctly set up. No feedback given. Assignments are not being graded to standard using assignment and Discussion Board rubrics. All students given uniformly high grades.	Assignment grading kept up to date with 1 or 2 assignments graded a couple of days late. DB grades posted one week after the session has ended. Instructor not using inline grading rubric for DB grades. Grade book is mostly set up correct with minor details missing such as weighted averages for all grades or other details. Little constructive feedback. Some assignments are not being graded to standard using assignment and Discussion Board rubrics.	Up to date grading on current assignments (no more than 7 days after due date). DB grades posted via rubric grading within 72 hours after the session has ended with feedback justification for grade. Grade book accurately matches the syllabus and set up correctly with 1000 points assigned to all graded elements within the course. Major assignment grades contains constructive feedback aligned with rubrics. Feedback addresses each element of the rubric. Papers grades contain detailed inline feedback. Instructors are not expected to correct all grammatical errors.	Up to date grading of assignments (72 hours after the due date); DB grades posted via rubric grading within 48 hours after the session has ended with feedback justification for grade. Provide students overall feedback for improvement for next assignment.

			All students held to grading standard with appropriate rigor based on the syllabus and rubrics.	

VITA

Born in Philadelphia, Pennsylvania to Eileen and the late Steven Noseworthy, Erin Thornbury is the oldest of two children. Her brother, Steven Noseworthy, lives with is wife, Jessica Noseworthy, and daughter, Brie, in the Pennsylvania subburbs of Philadelphia. Erin completed her public school education in the subburbs of New Jersey, graduating from Shawnee High School in 2000. She persued a Bachelors of Science in Art Education at The Pennsylvania State University, and was hired as an Education Assistant for School Programs at the Walters Art Museum in Baltimore, Maryland, just before her graduation. Erin spent her early career in museum education working with museum visitors of all ages. It was in this environment that she discovered a deep interest in instructional technology as a way to make information and learning more accessible and engaging. Inspired by this new interest, Erin completed a Masters of Art in Information and Learning Technology at the University of Colorado at Denver, while working full time as the Manager of Multimedia Interpretive Programs for the Hunter Museum of American Art in Chattanooga, Tennessee. It is at the Hunter Museum that she met her future husband, John Thornbury of Walden, TN; and it is this relationship that led her to linger in Chattanooga, eventually changing careers to join the University of Tennessee at Chattanooga as Senior Instructional Designer. In this position, Erin discovered a new passion for higher education, that spured her to continue her education and persue a doctoral degree in education. Erin's personal journey brought her new family to Seattle, Washington where she had the privelige of serving as the eLearning Director for City University of Seattle. After the birth of her son, Otto Henry Thornbury, Erin changed careers to persue a position as elearning Customer Success and Training Manager with Respondus Inc.; a position that has provided the space necessary for her current passion and most fulfilling work: being a mom.