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Using Educational Data Mining Techniques to Analyze the Effect of Instructors' LMS Tool Use Frequency on Student Learning and Achievement in Online Secondary Courses

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USING EDUCATIONAL DATA MINING TECHNIQUES TO ANALYZE THE EFFECT OF INSTRUCTORS' LMS TOOL USE FREQUENCY ON STUDENT LEARNING AND ACHIEVEMENT IN ONLINE SECONDARY COURSES

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Approved October 13, 2017

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ABSTRACT

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The pedagogy of teaching and learning has been changing since computers were first integrated into the classroom. As technology evolves, the evaluation of the instructional tool's effectiveness will continue to be an area of research need. The effectiveness of an instructional tool can be measured by student learning and achievement. Student learning and achievement was found to be most effective when the characteristics of active learning/engagement, frequent interaction, and feedback were present. The presence is provided by the instructor. Chickering and Gamson (1987) developed the Seven Principles for Good Practice (SPGP) in Undergraduate Education to improve teaching and learning.

The population for this study will be students enrolled in asynchronous online secondary school courses. In an online environment, the classroom is provided through a

Learning Management System (LMS). The instructor uses the tools provided in the LMS to interact with students. This study uses the SPGP that support the active learning/engagement, frequent interaction, and feedback characteristics for effective student learning. The LMS tools of updates, assignments, tests, and discussion boards support the SPGP principles 1, 2, 3, and 4. The student scores for pretest, posttest and semester final grade will be identified for each course. The pretest will be used as a control variable while posttest and semester final grade will be used as dependent variables in each hierarchical multiple regression. The independent variables for LMS tools will be determined by the instructors use frequency each semester. The courses are identified by curricular subject area and will be analyzed to determine if curricular subject area has any effect on the predictive power for both semester final grade and posttest scores.

This study employed a data mining procedure to determine if LMS tools could predict semester final grades (achievement) and posttest scores (learning). The findings suggest that the LMS tools can predict posttest scores but not semester final grades. Additionally, the study determined whether curricular subject area had an effect on the predictive power of the LMS tools. The findings of this study suggest that curricular subject area can predict the variance in semester final grades and posttest scores. The findings also suggest that there was unequal variance across curricular subject areas for the dependent variables. By categorizing the courses by curricular subject area, the predictive power of the LMS tools was positively affected. The LMS tools had large effect sizes in science and social studies for posttest scores when categorized by curricular subject area.

Additionally, the LMS tools updates, assignments, tests, and discussion boards varied in predictive strength and relationship to the dependent variables. The findings of this study indicated that the LMS assignment and discussion board tools were significant predictors with small positive effects for posttest scores. The findings also suggested that the LMS test tool was a significant predictor with a small negative relationship to posttest scores. The negative relationship found in this study contradicts the literature related to the frequency of tests in traditional classroom environments. The LMS test tool was primarily a learner-content interaction, whereas assignments primarily were a learner-instructor interaction and discussion boards were primarily a learner-learner interaction. The LMS update tool was a significant predictor for posttest scores but had a small positive relationship for semester-long courses and a negative relationship for year-long courses. The frequency of the LMS tools varied by curricular subject area. Specifically, the LMS assignment tool had the highest mean frequency across all subject areas.

The LMS tools, when added to pretest scores, contribute an additional 3% (SY1516 YL), 4% (SY1415 SL), and 8% (SY1516 YL) prediction of the variance of posttest scores with a small effect. The LMS tools for SY1415 YL predicted 14% of the variance with a medium effect. Specifically, the findings supported the linear positive relationship between assignments and discussion boards for posttest scores. The findings did not support that the LMS tools were a significant predictor for semester final grades when categorized by school year. By categorizing the courses by curricular subject area, the LMS tools were significant predictors for semester final grades and posttest scores. The LMS tools categorized by curricular subject area had small effects for semester final grades. The largest overall effect of the LMS tools was on posttest scores categorized by curricular subject area. Career and technical education SL was a small effect with 6% variance prediction. For medium effects the variance prediction was 20% for English YL, 17% for fine arts YL, 15% for math SL, and 16% for world languages YL. Finally, for the large effects, LMS tools added 29% variance prediction for science YL and 39% variance prediction for social studies YL. Therefore, curricular subject area does have an effect on the predictive power of LMS tools. This study provides a further example of educational data mining and the results that can be achieved with a strong pedagogical framework.

DEDICATION

Earning my doctorate degree was a personal goal and the support of my family made it possible. I dedicate the following to my mom, dad, and wife Stephanie. To my mom, who for the past 3 years would end each call with "So how is the writing going?" and always encouraged me to keep moving forward. To my dad, who read my dissertation many times and kept asking me to "dad proof" the language to make it more clear. And to my wife Stephanie, who agreed to marry me right in the middle of my dissertation writing, go on a honeymoon, and also allowed me to hide in my office and write in the evening and weekends. It will be nice to finally be able to plan our lives around something other than my writing schedule and deadlines. To my friends and family, I appreciate your support and understanding as I progressed through this journey. This dissertation was made possible by everyone's support and I thank you.

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CHAPTER I

Introduction

The pedagogy of teaching and learning has been changing since computers were first integrated into the classroom (Foley & Reveles, 2014; Strickland, 1989; Tarimo, 2016). As technology evolves, the evaluation of the instructional tool's effectiveness will continue to be an area in need of research (Delgado, Wardlow, McKnight, & O'Malley, 2015; Noeth & Volkov, 2004). In order to understand the effectiveness of an instructional tool, there must first be an understanding of what characteristics of learning are most effective. Student learning was found to be most effective when these fundamental characteristics were present: active engagement/learning, frequent interaction, and feedback (Van Amburgh, Devlin, Kirwin, & Qualters, 2007; Harden & Laidlaw, 2013; Phillips, 2005; Roschelle, Pea, Hoadley, Gordin, & Means, 2000; Sherman & Kurshan, 2005). The presence of the fundamental characteristics for effective learning is provided by the instructor through the instructional content. For effective learning to occur, the instructional content provided by instructors would need to use the most effective instructional practices that support active learning, frequent interaction, and feedback. The concept of effective teaching practices that lead to improved student learning was explored by Chickering and Gamson (1987).

Chickering and Gamson (1987) developed the Seven Principles for Good Practice (SPGP) in Undergraduate Education to improve teaching and learning. The SPGP are focused on effective instruction and consist of: encouraging contact between students and faculty, developing reciprocity and cooperation among students, using active learning techniques, giving prompt feedback, emphasizing time on task, communicating high expectations, and respecting diverse talents and ways of learning. These principles were developed for a traditional face-to-face environment and based on 50 years of research on how instructors teach and students learn (Chickering & Gamson, 1987). While the SPGP were originally developed for traditional face-to-face instruction, they have been applied to the study of newly developed instructional technologies (Chickering & Ehrmann, 1996; Dreon, 2013; Graham, Cagiltay, Lim, Craner, & Duffy, 2001; Guidera, 2004; Lai & Savage, 2013; Vogt, 2016). In order for the technological tools to be most effective they should utilize the SPGP to match instructional practice with the best technological tool (Chickering & Ehrmann, 1996). Research supports the idea that, if good instructional practice is linked with the most effective technological tool, it can better support student learning (Chickering & Ehrmann, 1996; Roschelle et al., 2000).

The SPGP and the fundamental characteristics of student learning share emphasis on active learning, frequent interaction, and feedback. There is supporting evidence that the SPGP enhance active learning and interaction which promotes engagement (Crews, Wilkinson, & Neill, 2015; Pascarella, 2006; Popkess, 2010; Thurmond & Wambach, 2004). However, it is challenging to track engagement and interaction in a traditional classroom (Kuh, 2003b). Through the use of technological tools, there are new opportunities for tracking interaction and engagement (Cox, 2013; Hill, 2015). These new opportunities for tracking interaction and engagement can be used by researchers to study the effect of the instructor's use of different technological tools. However, the effectiveness of technological innovation should be measured and defined by the improvement of student learning and achievement. In the study by Ferdig (2006), it was found that good technological innovation involved pedagogy, people, and performance.

Therefore, a framework for evaluating effective technology should include sound pedagogical technologies, with instructors who implement sound pedagogical principles to increase performance in student learning and achievement. If a technological tool is pedagogically well supported by instructors and designed technically with pedagogy in mind, the performance of the tool can be measured through student learning and achievement (Ferdig, 2006). Chickering and Gamson's SPGP support the active learning, frequent interaction, and feedback characteristics for effective student learning and have been applied pedagogically to technological tools (Chickering & Ehrmann, 1996; Dreon, 2013; Ferdig, 2006; Graham et al., 2001; Guidera, 2004; Lai & Savage, 2013; Vogt, 2016). Based on this support, the SPGP will serve as the theoretical framework for this study.

If a pedagogically supported technological tool has been shown to improve student learning and achievement, then the question that remains is how often or frequently should the tool be used by the instructor (Basol & Johanson, 2009; Gholami & Moghaddam, 2013; Gibbs, 2003; Kuh, 2003a; Peterson & Siadat, 2009). The quantity or frequency of instructional tool use is supported by the study by Kuh (2003b) that concluded "the more students practice and get feedback on their writing, analyzing, and problem solving, the more adept they become" (p. 25). The study by Kuh (2003b) was specifically interested in the frequency of the interactions, and the instrument used did not evaluate the quality of the interactions. The instrument used to evaluate the frequency of interaction in a traditional post-secondary school was the National Survey of Student Engagement (NSSE) (Kuh, 2003a). The NSSE includes questions based on the SPGP to evaluate student and staff responses on the use of activities that drive student learning outcomes through active learning, frequent interactions, and feedback (Chen, Lambert, & Guidry, 2010; Kuh, 2003a; Smulsky, 2012). The questions present in the NSSE were designed for the traditional classroom in the year 2000 and were revised in 2013 to include new measures and a student demographic indicator for online education status (National Survey for

Student Engagement, 2013). Even with the new online demographic indicator, it would be difficult to conclude that the NSSE would be a valid and reliable instrument to evaluate online secondary courses due to its being a self-report measure (Bowman, 2010; Campbell & Cabrera, 2011; Pascarella, Seifert, & Blaich, 2008). Due to the limitations of self-reported measures, the objective measure of frequency will be used to measure interaction and engagement through tool use for this study. Objective measures of student learning and achievement will be analyzed to determine if tool use frequency has any significant effect on student learning and achievement scores.

The interaction measured by the frequency of assessments in a traditional classroom was found to significantly affect student learning as measured by final grades (Martinez & Martinez, 1992). The final grade achievement in a course was shown to be improved by a higher frequency of assessments (Martinez & Martinez, 1992; Khalaf and Hanna, 1992). The studies by Martinez and Martinez (1992) and Khalaf and Hanna (1992) on the frequency of assessments have shown a benefit for student achievement, but there remains a need to understand the extent of the benefit and whether other instructional tools contribute to the improvement of student achievement. Proponents for frequent testing list the extent of benefits as: longer retention of material, preparation for high-stakes testing, extrinsic motivation, student preparation on tests, smaller amounts of materials for deeper processing, more classroom discussion, reduced test anxiety, useful feedback for the school on student performance, and increased classroom attendance (Gholami & Moghaddam, 2013). While the benefits may differ across studies, a meta-analysis by Gocmen (2003) determined that frequent testing was beneficial to student learning and academic achievement in a traditional face-to-face classroom. Therefore, the frequency of tool use could be used to determine the effect on student learning and achievement.

In the meta-analysis for frequency of assessment tool use, Gocmen (2003) also reviewed curricular subject area and, while the effect sizes were found not to be significant, social sciences accounted for the majority of studies and had the largest mean effect size. Basol and Johanson (2009) in their meta-analysis found the math subject area had the largest mean effect size. Not all subject areas were accounted for in these meta-analyses, and the research studies used in the meta-analyses did not compare frequency of assessments across subject areas, instead primarily focusing on a single course (Basol & Johanson, 2009; Gocmen, 2003). This study is designed to determine whether curricular subject area has an effect on student learning and achievement when comparing frequency of tool use across subject areas for similarly designed courses at a single institution. It should be noted that the studies analyzed in the meta-analyses were primarily from traditional college-level institutions and were focused on the instructor's use of assessment tool (Basol & Johanson, 2009; Gocmen, 2003). This study is designed to extend frequency of tool use research beyond assessments to other instructional tools and to examine frequency of tool use within the online secondary school environment.

While research in the early twentieth century focused on computers in the classroom, a new form of education using the internet was being developed. Online learning built upon the concept of correspondence courses and developed a system to deliver the content through the internet. Online learning expanded from thinking of technology as a tool, to thinking of technology as a necessary requirement for instruction. Consensus on the viability of online learning has allowed researchers to move beyond comparing online and traditional classrooms to examining how instructional interventions compare within the same environment (Borokvskia, Tamim, Bernard, Abrami, & Sokolovskaya, 2012). In order to deliver instruction over the internet, many technologies are required, but continued research is needed to determine which tools are pedagogically supported and have the greatest effect on student learning and achievement (Noeth & Volkov, 2004; Pascarella, 2006; Peltier, Schibrowsky, & Drago, 2007).

The most common technologies used to deliver instruction over the internet include: learning management system (LMS), learning content management system (LCMS), and course management system (CMS). An LMS will include the basic tools that allow for communication, collaboration, content delivery, and assessment. An LMS is different from a LCMS. An LCMS is used primarily for the development, maintenance, and storage of instructional content. An LCMS can deliver content, but it is usually missing the course administrative functions of an LMS. These differences typically allow an instructional designer to build interactive web-based content in an LCMS which would then be delivered to students within an LMS course (Ninoriya, Chawan, & Meshram, 2011).

A CMS focuses on managing student enrollment and performance, and on creating and distributing course content. This term is often used interchangeably with an LMS, but they are not exactly the same. A CMS has built-in content authoring tools and can deliver content, but an LMS is often more robust in the content types it can deliver and contains additional reporting to assist instructors in improving student performance. When implementing a learning strategy, an LMS is the best option. When developing learning content, an LCMS would be the more appropriate choice (Giurgiu, Bârsan, & Mosteanu, 2014; Ninoriya et al., 2011). The acronym CMS also causes some confusion among researchers since it is also used to describe a content management system. A content management system has components similar to those of an LCMS but focuses on the storage of the individual files used to create the learning content (Guirgiu et al., 2014). Systems such as Moodle and Blackboard that were originally known as a CMS have begun using LMS to describe their product (Forouzesh & Darvish, 2012; Muhsen, Maaita, Odah, & Nsour, 2013). Learning systems continue to evolve and future systems will likely create new terms to describe them as they evolve. While the CMS and LCMS have their place in online education, the LMS is the most commonly used and is a critical component for developing an online learning environment (Park, 2014). The online secondary school population selected for this study received its instruction through an LMS.

The LMS used in this study provides tools for updates, assignments, tests, and discussion boards. These LMS tools support pedagogical tasks that would be completed in a traditional classroom. An update serves the same purpose as an instructor making an announcement at the beginning or end of class. An assignment is similar to the instructor's assigning work outside the classroom that requires writing and research, to be submitted by the student at a later date. A test allows the instructor to assess the knowledge of the students through a series of true/false, multiple choice, ordering, matching, fill-in-the-blank, short answer, and/or essay questions. A discussion board simulates a group discussion within the classroom on a topic provided by the instructor. The LMS provides an environment and location for learner-learner, learner-instructor, and learner-content interactions to occur (Goosen & van Heerden, 2015). The LMS could then be used to track the number interaction points by the frequency of tools used by instructors in the course. In terms of evaluating the frequency of interaction, research has shown that the LMS may play a role in activating interactive behaviors (Bernard et al., 2009; Cechinel, 2014; Coates, James, & Baldwin, 2005; Goosen & van Heerden, 2015; Hashim, Hashim, & Esa, 2011).

In a traditional classroom, interactions between students and instructors is difficult to quantify, but the LMS provides the ability to track the frequency of interaction through the instructor's use of updates, assignments, tests, and discussion boards. Previous research on the frequency of interactions in a traditional classroom focused on assessments such as tests (Basol & Johanson, 2009; Gocmen, 2003; Khalaf & Hanna, 1992; Martinez & Martinez, 1992). The study of online courses by Picciano (2002) found that higher interaction in discussion boards led to higher performance on the final exam and written assignment. More frequent assessments in the form of tests have been shown to improve student achievement in traditional classrooms, but frequency of tool use research did not consider the influence of other interactive events (Basol & Johanson, 2009; Gocmen, 2003; Khalaf & Hanna, 1992; Martinez & Martinez, 1992). The frequency of instructional tool use can be extended to LMS tools in an online environment (Stamm, 2013; Vogt, 2016). However, instructional technology research should focus on understanding why and how the LMS tools impacted student learning (Ferdig, 2006).

An LMS provides a unique opportunity for evaluating student learning due to the storage of student data relating to the interaction event, time spent on interaction, date of access, grade received, and other useful data. The LMS logs provide data that can be analyzed through Educational Data Mining (EDM). The study by Romero and Ventura (2007) explained that current data mining methods used clustering and pattern recognition to associate students into various groups. Through clustering and pattern recognition group associations, an instructor can make small but immediate changes for individuals. To evaluate instructional changes that affect the entire classroom, predictive analyses can be used to determine the impact of the changes on student learning and achievement. With access to data through the LMS and the ability to analyze the data, K-12 schools and districts are starting to use experimental predictive analyses to detect areas of instructional improvement (U.S. Department of Education, Office of Educational Technology, 2012).

Instructional improvement is evaluated in terms of student learning outcomes, but an LMS can deliver instruction through various tools and methods, which is why the U.S Department of Education's Office of Educational Technology (2012) encouraged research that focused on two areas. The first area of focus is on methods of using student information data and aligning data across systems. The second area of focus is on repurposing predictive models developed for one educational institution and applying them to another educational institution. Repurposing predictive models is difficult due to varying students, administrative policies, course programs, types of institutions, and learning management systems (Lauría & Baron, 2011; U.S. Department of Education, Office of Educational Technology, 2012). This study will reduce the difficulties for repurposing predictive models by using LMS tools that are available in all currently available learning management systems. Based on the research focus areas outlined by the U.S Department of Education's Office of Educational Technology, this study will use predictive analysis and data mining techniques to evaluate the impact of LMS tools on student learning and achievement.

Based on literature review of recent research studies and reports, the following research gaps were identified: objective measures of student learning (Eom, 2012; Islam, 2016), lack of rigorous studies of the effectiveness of online learning in K-12 environments (U.S. Department of Education, 2010), improving student learning through student engagement (Carle, Jaffee, & Miller, 2009), analyzing data to improve instructional content (U.S. Department of Education, Office of Educational Technology, 2012), and research-based educational predictive models (Siemens & Baker, 2012). To address each of the identified research gaps, this study was designed for an understudied population using objective measures that are data mined from educational systems and analyzed using predictive regression models to improve instructional content. The population for the sample specifically focused on fully online asynchronous secondary courses to provide research data for an under-studied population and to determine if higher education principles can be applied to online secondary instruction. The objective measures of the frequency of interaction through LMS tool use provides quantitative empirical data that are not self-reported through surveys or interviews. The data will be analyzed to determine which tools are the most predictive of student learning and achievement. The results of the data analysis could then be used to improve student learning and achievement through changes in instructional content.

The framework for this study uses Chickering and Gamson's SPGP and will apply the principles to online secondary courses. The SPGP have been used as a framework for studying online teaching and learning by other researchers (Dreon, 2013; Graham et al., 2001; Guidera, 2004; Lai & Savage, 2013). In an online environment, the instructor uses the tools within the LMS to interact, engage, and provide feedback to students. The instructional tools provided within the LMS have been specifically studied by researchers using the SPGP as a theoretical framework (Dreon, 2013; Lai & Savage, 2013; Phillips, 2005; Vogt, 2016; Woods, 2004). SPGP Principles 1, 2, 3, and 4 support the effective student learning characteristics of active learning/engagement, frequent interaction, and feedback. Each tool provided by the LMS was included in the study based on its support of SPGP Principles 1, 2, 3, and 4. SPGP Principles 1, 2, 3, and 4 all require interaction between students and instructors. The frequency of interaction can then be measured by the number of times the LMS tools are used by instructors in an online course.

The LMS tools of updates, assignments, tests, and discussion boards support the pedagogical SPGP Principles 1, 2, 3, and 4. The frequency of each interactive LMS tool used in the online secondary courses will be analyzed to measure the effect on student learning and achievement. The frequency of updates will be measured by the number of updates posted by the instructor in an 18 week-long semester. The frequency of assignments, tests, and discussion boards will be measured by the number of each created by the instructor and published for students to complete. Student achievement will be measured through the semester final grade score. Student learning will be measured using a pretest at the beginning of the course and a posttest at the end of the course. This study will determine if LMS tool use frequency can significantly predict student learning and student achievement scores. Previous LMS tool predictive research did not include curricular subject area as a possible predictor, and the meta-analyses that have been conducted have not addressed online courses (Basol & Johanson, 2009; Gocmen, 2003; Lai & Savage, 2013; Stamm, 2013; Vogt, 2016). This study will research whether the frequency of LMS tool use significantly varies by curricular subject area and whether curricular subject area significantly adds to the predictive equation. The study will also determine if LMS tool use frequency varies by course length for predicting posttest scores. The results will determine whether the frequency of LMS tool use by an instructor in an online secondary course significantly affects student final grade and posttest scores. The results will also provide a new EDM model for future experimental research to determine if frequency of LMS tool use by instructors also has a causal effect.

Statement of the Problem

The number of students taking online courses has been increasing steadily each year. Queen and Lewis (2011) of the U.S. Department of Education found that there were an estimated 1,816,400 enrollments in online K-12 courses. The 1,816,400 enrollments were collected from traditional schools that provided online course options to their students. The enrollments did not include the International Association for K-12 Online Learning's (iNACOL) estimate of 200,000 full-time virtual school students during that same time period, which has since grown to 310,000 full-time virtual school students in 2012-2013 (Watson, Pape, Murin, Gemin, & Vashaw, 2014). Full-time virtual school students receive all of their courses online, which would add to the total number of online K-12 course enrollments. The millions of students taking online classes prompted the comparison of online learning to traditional face-to-face classroom. In its meta-analysis, the U.S. Department of Education (2010) did not find a significant difference in student learning outcomes between online learning and traditional face-to-face instruction. While the comparison was well researched, the U.S. Department of Education (2010) also stated that "few rigorous research studies of the effectiveness of online learning for K-12 students have been published" (p. xiv). Many of the studies that compare online courses to traditional face-to-face courses assess a wide variety of outcomes and have yielded little, if any, evidence to suggest that online learning is more or less effective than face-to-face learning (Lim, Kim, Chen, & Ryder, 2008; Parker, 2015; Schmidt, 2012).

While there was not a significant difference in learning outcomes, a fundamental flaw in conducting comparison research is that, even if exactly the same media are used, they are used for different purposes, which creates inequality between treatments (Bernard et al., 2004). In essence, comparing different delivery methods is difficult due to the differences in design and purpose. Comparison studies have shown that the research need has moved from comparing online and traditional instruction, to understanding the course design and implementation by instructors in online courses and its effect on learning outcomes (Borokhovski et al., 2012; Caldwell, 2006; Parker, 2015; Swan, Matthews, Bogle, Boles, & Day, 2012; U.S Department of Education, 2010).

The annual K-12 digital learning review by iNACOL identified that online learning environments commonly use a learning management system (LMS) as a delivery tool (Watson et al., 2014). But, despite the popularity and critical role of the LMS, relatively little research has examined the relative influence on objective measures of student learning (DeNeui & Dodge, 2006; Eom, 2012). The use of an LMS would then have pedagogical influence on the design of instruction, but the effects or influence is not well-defined or known (Bongey, 2012; Coates et al., 2005). Coates, James, and Baldwin (2005) would agree that learning management systems are not pedagogically neutral technologies and that, through their very design, they influence and guide teaching. The lack of research can be corrected easily because student learning behaviors are recorded and stored within an LMS and can be measured objectively (Hung, Hsu, & Rice, 2012). But instead of studying student learning behaviors, adoption and utilization of the LMS has been a major focus for research (Islam, 2016; Park, 2009; Venter, van Rensburg, & Davis, 2012).

When evaluating student learning, it was found that self-reported data through course evaluations were not consistent with learning behaviors and the lack of direct observation compounded the inconsistency (Bowman, 2010; Hung et al., 2012). The study by Hung, Hsu and Rice (2012) used course evaluations and activity data mined from the LMS to determine if engagement had an impact on K-12 student final grade performance, and it was found that more highly engaged students had higher performance. Comparing self-reported and objective measures shows that student perception data, when used solely to inform strategic decisions, can result in a misrepresentation of the data and flaws in decision-making (Bowman, 2010; Ferdig, 2006; Hung et al., 2012; Islam, 2016). Using self-reported data due to the cost and time limitations needed for more objective measures is no longer the only option available to researchers. Data mining of LMS data can provide a look at both the student and instructor behaviors in an online environment. This study will be specifically analyzing the LMS data to determine the frequency of tool use behaviors of instructors. As previously stated, student learning was found to be most effective when the fundamental characteristics of active engagement/learning, frequent interaction, and feedback were present. The LMS tools provide instructors with interaction and feedback with their students in an online environment. The frequency of interaction and feedback exists as objective data within the LMS, and therefore frequency data are available for use in research studies.

Purpose of the Study

The purpose of this quantitative study is to evaluate student learning and achievement in online secondary courses using the frequency of LMS tool use by instructors as an objective measure. Various studies of learning management systems have used adoption and utilization measures to evaluate the impact of the LMS on instruction; the instruments used are largely self-reported measures and focused on the perceptions of students and staff (Islam, 2016; Lee, 2009; Liaw, 2008; Limayem & Cheung, 2011). This study will not use self-reported data and will use objective frequency of use data retrieved from the LMS. Islam (2016) was not able to get objective data on actual usage and grades due to privacy, but suggested that future research could evaluate using objective measures. A study of objectively measured online instructional events supported by pedagogically aligned LMS tools would fill the gap in knowledge between student self-reported presence of the events and student learning and achievement outcomes (Ferdig, 2006; Islam, 2016; Nelson, 2000).

In order to pedagogically support the objective measures available in an LMS, a relationship between instructional frameworks and LMS tools is required. Researchers have considered the SPGP to be instrumental in developing theoretical frameworks to study instructional immediacy, student engagement, student attrition, online learning, and instructional technology (Chickering & Gamson, 1999, Dreon, 2013; Graham et al., 2001; Guidera, 2004; Hathaway, 2013; Hutchins, 2003; Tirrell, 2009). The Seven Principles for Good Practices are used as a guide to improve teaching and learning (Chickering & Gamson, 1987). George Kuh even wrote a personal communication to the authors of the SPGP that there are many teachers implementing the principles and "So [even if] folks may not be wearing a laminated SEVEN PRINCIPLES card around their necks, the principles have and will continue to have a substantial impact."(Chickering & Gamson, 1999, p. 80). While the SPGP are useful in research and by practical application by instructors, they also contain the characteristics for effective student learning. The SPGP provide principles of effective instruction and student learning that can be applied to technology (Chickering and Ehrmann, 1996). The SPGP were found to be present in online instructional tools provided within an LMS (Dreon, 2013; Lai & Savage, 2013; Phillips, 2005; Woods, 2004). The LMS tools of updates, assignments, tests, and discussion boards are pedagogically supported by the SPGP, and a characteristic of effective student learning is frequent interaction. If students interact with their instructors through the LMS tools, then the frequency of LMS tools used by the instructor can be analyzed to determine its effect on student learning and achievement.

Research Questions

This study used Chickering and Gamson's SPGP to determine the pedagogical support for the interactive tools provided by the LMS in online secondary schools. The LMS tools of updates, assignments, tests, and discussion boards support SPGP Principles 1, 2, 3, and 4. These principles support the effective student learning characteristics of active learning/engagement, frequent interaction, and feedback. The frequency of interaction will be measured by the count of each LMS tool used by instructors in a semester-long course. This study will also research whether the frequency of LMS tools used varies significantly by curricular subject area and whether curricular subject area significantly adds to the predictive equation. The following research questions will be explored:

1. To what extent does the frequency of LMS update, assignment, test, and discussion board tools used by instructors predict semester final grade achievement by students in online secondary courses after controlling for prior learning?
2. To what extent does the frequency of LMS update, assignment, test, and discussion board tools used by instructors predict posttest learning by students in online secondary courses after controlling for prior learning and does the effect vary by course length?
3. To what extent does curricular subject area in addition to the frequency of LMS tool use affect the prediction of student achievement and student learning in online secondary courses?

Advances in online learning have created more trackable data, which can be used to make predictions more accurate (Corrigan, Glynn, McKenna, Smeaton, & Smyth, 2015). The frequency of updates, assignments, tests, and discussion boards is not currently tracked as a quantitative value in an LMS but could be added easily by the LMS developers. This study will show if the frequency of LMS tool use is worth displaying to instructors. Generally, good teaching and learning depends on the method of delivering information, which makes it necessary to determine the influence of the LMS on the pedagogical goals of teaching and learning (Lai & Savage, 2013). This study's use of Chickering and Gamson's SPGP to evaluate the LMS tools will provide the pedagogical framework for its influence on teaching and learning in an online environment.

Specifically, this study will determine if the frequency of LMS tools of updates, assignments, tests, and discussion boards have predictive validity in regard to student achievement as final grades and student learning as posttest scores. The study has two dependent measures due to the inherent subjectivity present in final grades, which is why the additional objective posttest measure was included for research comparison. Having dependent measures of achievement and learning will allow the researcher to show how the independent frequency of LMS tool use measures varies between achievement and learning. Frequency of LMS tool use is an objective measure and, as emphasized by previous research on LMS tools, objective measures are needed to analyze the effect on student learning and achievement (DeNeui & Dodge, 2006; Eom, 2012; Hung et al., 2012; Islam, 2016). If predictive analysis is possible, courses can be evaluated objectively and future experimental research can evaluate the change in the frequency of LMS tool use to determine their causal relationship with student achievement and student learning.

Limitations of the Study

This study is limited, due to the quantitative design for evaluating the frequency of LMS tool use, which measures the quantity, not quality, of use. All occurrences of the LMS updates, assignments, tests, and discussion board tools used within the course were included in the frequency measure and the quality of the content provided in the LMS tool was not evaluated. When collecting the frequency of updates, the quality of information provided by the instructor was not evaluated. An evaluation instrument to assess the quality of the information provided by the LMS update tool would be needed to determine if an update should be included in the frequency measure. Therefore, all updates posted by the instructor were included in this study. When collecting the frequency of assignments, the instructional quality provided by the instruction through the LMS assignment tool was not evaluated. An evaluation instrument to determine the quality of instructional content provided through the LMS assignment tool would be needed to determine if the assignment should be included in the frequency measure. Therefore, all assignments available to students within the course were included in this study. When collecting the frequency of tests, the quality of the test design was not evaluated. An evaluation instrument to determine the instructional quality of the test design would be needed to determine if the test should be included in the frequency measure. Therefore, all tests available to students within the course were included in this study. When collecting the frequency of discussion boards, the quality of the instructional content provided by the instructor was not evaluated. The number of posts by the instructors and students was not collected, only the number of discussion boards created within the course by instructors. An evaluation instrument to determine the quality of the instructional content provided by the discussion board would be needed to determine if the discussion board should be included in the frequency measure. Therefore, all discussion boards available to students within the course were included in this study. The frequency data are limited due to a change in LMS for the beginning of school year 2014-2015. The previous LMS contract was discontinued and there is no access to existing LMS data prior to June 2014.

The semester final grade as an achievement measure has limitations due to instructor subjectivity. The semester final grade score can vary, depending on the weight assigned by instructors for various assessments or the weight given to the final exam. Assignments, discussion boards, and test essay questions all have subjective components for scoring purposes that affect the overall final grade for the course. Due to the semester final grade limitations, the objective pretest and posttest scores will also be included in the analyses to account for instructor subjectivity.

Delimitations of the Study

Delimitations were determined when reviewing the tools available within an LMS and available research literature on LMS tools. The tools provided by an LMS can vary, but certain basic instructional tools exist within all systems. These basic tools are announcement/updates, assignment upload location, tests, discussion boards, web links, and pages. Using the basic LMS tools available in all systems allows this study to be applied more easily and recreated by researchers regardless of the specific LMS provided by their institution. Proprietary LMS tools that exist only within a specific LMS provider were not considered for this study. Third party and external tools were not considered as they require additional cost, setup, and configuration outside the LMS environment provided by the institution. This study is focused on the characteristics of instruction that lead to effective learning. Therefore, each of the basic LMS tools was evaluated for the presence of interaction and the measurement of the interaction assessed by the frequency of LMS tools used by instructors in a semester-long course.

Pages and web links are considered course content and could be multimedia activities, static text content, embedded videos, textbook links, external websites, and/or images. This variability in what was provided through web links and pages would require a subjective measure to determine if active and engaged learning was taking place. In terms of measuring web links, the LMS data do provide the number of times a web link was clicked, but does not specify whether each student clicked the web link. Content pages built within the LMS provided by the institution selected for this study did not have tracking information and it was not possible to determine if a student viewed the content on the page or the amount of time spent on the page. The focus of this study is measuring interaction points with instructors and students and therefore the LMS tools of pages and web links were excluded from this study. The LMS tools of updates, assignments, tests, and discussion boards were present in all courses studied and supported student engagement and interaction. The Seven Principles for Good Practice were also present in updates, assignments, tests, and discussion boards which supports the idea that these four LMS tools were pedagogically designed and should be included in the study.

The design of the study also created delimitations for the data collected from the LMS. The LMS tools are implemented by the instructor at the course level. Therefore, the frequency of LMS tools used in the course is defined by the instructor. Student data related to LMS tools were not collected, as they would not change the frequency of LMS tools in the course. Student data are considered outside the scope of this study, and course-level data from the LMS set the boundaries for the data that can be analyzed in this study. The course data also contained delimitations, due to the fact that some of the newer courses that were procured by the organization used a third-party LMS to provide assignments, tests, and discussion boards to students. The contract with the third-party vendors did not allow access for LMS database queries. The course content provided by the third-party LMS also did not contain pretest or posttest assessment. For these reasons, courses that used the third-party LMS for content delivery were not included in this study.

The environment and population selected for this study is another delimitation. The educational environment selected for the study is online education. The population being studied enrolls in an online course, which requires a portion of the student's school day to be assigned to a space with computers to complete online coursework. These students would not be considered full-time virtual school students, but the course is offered fully online and all interaction takes place in the online environment. The population being studied consists of secondary school students earning American high school diplomas. The study is further delimited by the population being located around the world in various time zones. The study is further delimited to English-speaking subjects.

Definition of Terms

Assignees: An LMS database field that shows if a graded item has been individually assigned. Graded items that are individually assigned are not completed by the entire class. If a graded item has data in this field, it will not be included in the frequency calculation.

Assignment: An LMS tool for assessment of knowledge that requires students to complete offline work and submit their work to a specific assignment by uploading the work from their computer to the LMS.

Asynchronous Instruction: A form of education, instruction, and learning that does not occur in the same place or at the same time (Hidden Curriculum, 2014).

Discussion Boards: An LMS tool that provides an area where students can communicate through responses and replies to responses about a specific topic at different times. Also known as forums or message boards.

Dropbox Submissions: An LMS database field that contains an integer of the number of submissions in an assignment's dropbox. A number greater than 0 in this field shows that students submitted work to the assignment. If this field is greater than 0, the assignment will be included in the frequency calculation.

Educational Data Mining: An emerging discipline for developing methods for exploring the unique types of data that come from educational systems. The need to consider pedagogical aspects of the learner and system sets it apart from other data mining domains (Romero & Ventura, 2007; Romero, Ventura, & Garcia, 2008).

Frequency: This term will be used in a statistical manner to define the number of times the event occurred within the length of the course.

Grading Category: An LMS database field that contains an integer identifier for the category of the graded item. A category is defaulted to ungraded until an instructor creates a new name for a graded category, such as “assignment,” which will then make the item graded.

Grading Period: An LMS database field that contains an integer identifier for the grading period of the graded item. The instructor chooses the grading period for the item from a selection menu that contains six grading periods with specific start and end times for each school year: Quarter 1, Quarter 2, Sem 1 Exam, Quarter 3, Quarter 4, and Sem 2 Exam.

Interaction: The learner’s engagement with the course content, other learners, the instructor, and the technological medium used in the course (Thurmond, 2003).

Last Updated: An LMS database field that contains a time and date when an update is posted in the course. This date in this field will be used to determine the semester for the update tool frequency calculation.

Learning Analytics: The use of data mining, interpretation, and modeling to improve pedagogical design and student learning (Johnson, Smith, Willis, Levine, & Haywood, 2011).

Learning Management System (LMS): The framework that handles all aspects of the learning process and the infrastructure that delivers and manages instructional content (Watson & Sunnie, 2007).

Online Learning: Learning that takes place partially or entirely over the Internet (U.S. Department of Education, 2010).

Published: An LMS database field that contains a value for whether the item is available/published or hidden from students. The value is "0" for hidden and "1" for published.

Student Achievement: This study will define student achievement as semester final grades.

Student Learning: To measure growth, this study will be using pretest and posttest scores to evaluate the change.

Synchronous Learning: A form of education, instruction, and learning that occurs in the same place and at the same time.

Tests: An LMS tool for assessment of knowledge that requires a student to answer questions. Question types can include true/false, multiple-choice, matching, ordering, fill-in-the blank, short-answer, and essay.

Title: An LMS database field that contains the name provided by the instructors for an assignment, test, and discussion board.

Type: An LMS database field that contains the type of the graded item as assignment, assessment, or discussion. This field will be used to separate the data by item type for frequency calculation.

Update: An LMS tool that allows the instructor to post information within the course. It can have options such as allowing students to comment or to receive a copy in their email. It may also be known as an announcement in some LMS systems.

CHAPTER II

Literature Review

Chickering and Gamson's Seven Principles for Good Practice

In 1987, Chickering and Gamson published the Seven Principles for Good Practice (SPGP) in Undergraduate Education, which have since been adopted by many institutions (Bieniek & Pratt, 2004; Chickering & Gamson, 1999; Duquesne University, n.d.; Page & Mukherjee, 1999; Winona State University, 2009). Chickering and Gamson (1987) developed the Seven Principles for Good Practice in Undergraduate Education to improve teaching and learning. The principles were developed for a traditional face-to-face environment and based on 50 years of research on the way instructors teach and students learn (Chickering & Gamson, 1987). Researchers have considered the Seven Principles for Good Practice to be instrumental in developing theoretical frameworks to study instructional immediacy, student engagement, student attrition, online learning, and instructional technology (Chickering & Gamson, 1999, Dreon, 2013; Graham et al., 2001; Guidera, 2004; Hathaway, 2013; Hutchins, 2003; Tirrell, 2009). George Kuh even wrote a personal communication to the authors of the SPGP that there are many teachers implementing the principles and "So [even if] folks may not be wearing a laminated SEVEN PRINCIPLES card around their necks, the principles have and will continue to have a substantial impact."(Chickering & Gamson, 1999, p. 80).

The following is a list of the Seven Principles for Good Practice as outlined by Chickering and Gamson's (1987) study:

1. Encourages contact between students and faculty.
2. Develops reciprocity and cooperation among students.
3. Uses active learning techniques.

4. Gives prompt feedback.
5. Emphasizes time on task.
6. Communicates high expectations.
7. Respects diverse talents and ways of learning.

The SPGP are intended to be used as guidelines for instructors, administrators, and students to improve teaching and learning (Chickering & Gamson, 1987). The numbered order is not hierarchical in nature. Each principle can be used independently, but when the principles are used together they can have a greater effect (Chickering & Gamson, 1987). The effect of the SGPG is what Chickering and Gamson (1987) labeled the six powerful forces in education: activity, cooperation, diversity, expectations, interaction, and responsibility. This study will attempt to analyze the effect of educational forces of activity, cooperation, and interaction.

SPGP principle 1. The first principle encourages contact between students and faculty. Chickering and Gamson (1987) considered frequent interaction to be the most important factor in student involvement. The relationship between motivation and student learning and achievement is complex, but generally the higher the motivation of the student, the greater the effort on the task, which leads to better performance (Pintrich, 2003; Ross, 2008; Weiner, 1985). Higher involvement has been associated with more engagement, more learning, and higher levels of achievement (Hidi & Harackiewicz, 2000; Pintrich, 2003). SPGP principle 1 helps students get through rough times and keep working and the more frequently this occurs the more encouragement they receive (Chickering & Gamson, 1987). SPGP principle 1 is considered important by Chickering and Gamson and will also be considered an important principle in this research study.

SPGP principle 2. The second principle develops reciprocity and cooperation among students. Learning is enhanced when it is collaborative and social (Chickering & Gamson, 1987). Working with others often increases involvement and, through sharing ideas and responding to others, it can improve thinking and deepen understanding (Chickering & Gamson, 1987; Jin, 2005; Reio & Crim, 2006). Chickering and Gamson used previous research to inform the SPGP, and the social component of this principle relates to Bandura's (1986) social cognitive theory, which declares learning as a social process where interactions can lead to student achievement. Vygotsky (1986) also states that social interaction is a natural human need and is an important factor in the development of learning processes. SPGP principle 2 is focused on improving social and collaborative interactions between students, with the goal of enhanced learning.

SPGP principle 3. The third principle uses active learning techniques. Learning is not a spectator sport. Students need to take what they learn and relate it to their past experiences to make it part of themselves (Chickering & Gamson, 1987). Active learning instructional strategies may vary, but instructors try to create an environment that engages students through critical thinking and exploration of new ideas (Collard, 2009). One approach to active learning techniques is the use of frequent assessment to provide students and instructors with a measurement of achievement and comprehension (Van Amburgh et al. 2007; Casem, 2006; Donovan, Bransford, & Pellegrino, 1999). Another approach is to design assignments that engage students in higher-order thinking and problem-solving (Phillips, 2005, Popkess, 2010). SPGP principle 3 is focused on engaging students in active learning and not passive lecture or reading (Chickering & Gamson, 1987; Collard, 2009).

SPGP principle 4. The fourth principle gives prompt feedback. Students need timely and appropriate feedback on their performance to assess their own knowledge and competence (Chickering & Gamson, 1987). In addition to having prompt feedback, students need frequent opportunities to perform and learn how to use feedback to improve performance (Chickering & Gamson, 1987; Collard, 2009; Crews et al., 2015). Feedback can be provided by the content, instructor, and other learners (Phillips, 2005). Content feedback can be provided through assessments with right-or-wrong answer guidance (Chickering & Gamson, 1987; Phillips, 2005; Popkess, 2010). Instructor feedback can be provided through comments on graded work, grade received, and instructor-generated rubrics (Chickering & Gamson, 1987; Phillips, 2005; Popkess, 2010). Learner-to-learner feedback can be provided through peer-reviews and group discussions (Chickering & Gamson, 1987; Phillips, 2005; Popkess, 2010). SPGP principle 4 is focused on how feedback is central to the learning process and improving student performance (Chickering & Gamson, 1987).

SPGP principle 5. The fifth principle emphasizes time on task. There is no substitute for time on task, and students' knowing how to use their time well is critical to effective learning (Chickering & Gamson, 1987). The instructor has an important role in helping students understand the time limits and expectations for time on task to complete the coursework (Collard, 2009). The instructor needs to communicate time expectations to students through a syllabus, due dates, and clear instructions that allow students to use time management techniques (Crews et al, 2015; Collard, 2009; Grant & Thornton, 2007). Instructors emphasizing time on task utilize classroom management strategies to limit off-task behaviors (Shechtman & Leichtentritt, 2004). SPGP principle 5 is focused on students on task behaviors and the instructor's role is to emphasize time on task through classroom management strategies.

SPGP principle 6. The sixth principle communicates high expectations. Instructors and institutions that communicate their high expectations for performance can become a self-fulfilling prophecy (Chickering & Gamson, 1987). High expectations alone will not automatically result in higher student achievement. The presence of talent, motivation, and experience is also needed (Scott & Tobe, 1995). Communicating high expectations has elements similar to emphasizing time on task, as both clearly articulate the expectations of the instructor (Chickering & Gamson, 1987). Communication of high expectations can occur through the course syllabus, learner objectives, and providing examples of work that meets the instructor's high expectations (Crews et al., 2015; Graham et al., 2001; Grant & Thornton, 2007). It is also important to understand that not all students will have the same level of talent and motivation, so instructors may need to tailor assignments and expectations so that each student can succeed (Scott & Tobe, 1995). SPGP principle 6 is focused on motivating students to succeed through communicating the high expectations of the instructor for individual student performance.

SPGP principle 7. The seventh principle respects diverse talents and ways of learning. Students have diverse talents, educational backgrounds, and skills, which will require instructors to use diverse teaching methods and provide individualized learning opportunities (Chickering & Gamson, 1987; Collard, 2009). Respecting diverse talents and communicating high expectations share a common element of modifying instruction based on the individual. Using individualized instruction requires more time from the instructor on administering tests, diagnosing learning needs, and providing individual guidance (Pena, 2007). The ways of learning or learning styles has been prolific in literature but lacks empirical evidence that changing instruction for visual, auditory, or kinesthetic learning styles will improve learning (Rohrer & Pashler, 2012). It is still useful for instructors to understand that students have diverse talents and that using a variety of instructional strategies to engage students is still a good practice (Zwaagstra, 2013). SPGP principle 7 is focused on the talents and skills an individual student brings to the classroom and the strategies an instructor can implement.

While the SPGP were developed for traditional face-to-face instruction, they have been applied in the study of new technologies (Chickering & Ehrmann, 1996; Dreon, 2013; Graham et al., 2001; Guidera, 2004; Lai & Savage, 2013). Technology is a broad term and involves the use of technical processes to accomplish a task. This study is specifically interested in the field of instructional technology. Chickering and Ehrmann (1996) applied the SPGP to instructional technologies used in online learning. The SPGP has been used by other researchers as a framework for studying online teaching and learning (Dreon, 2013; Graham et al., 2001; Guidera, 2004; Lai & Savage, 2013). In online learning, instructional technology is needed to deliver instruction and one of the technological tools used is the learning management system. The instructional tools provided within the LMS have been specifically studied by researchers in using the SPGP as a theoretical framework (Dreon, 2013; Lai & Savage, 2013; Phillips, 2005; Vogt, 2016; Woods, 2004). This study will focus on the SPGP that support the frequent interaction characteristic of effective student learning. Interaction between students and faculty is supported by SPGP Principles 1, 2, 3, and 4, and each tool provided by the LMS is evaluated based on its support of these principles. The frequency of interaction can then be measured by the number of times the LMS tools are used in an online course. But, in order for the power of new technologies to be fully realized, they should utilize the SPGP to match instructional practice with the best technology (Chickering & Ehrmann, 1996). If a good instructional practice is linked with the most effective technology, it can better support student learning (Chickering & Ehrmann, 1996; Roschelle et al., 2000).

Defining Instructional Technology

The Association for Educational Communications and Technology (AECT) 1977 definition was geared more toward educational technology than instructional technology but included a depth and breadth to the definition that included the core concepts of the systematic design of instruction. “Educational technology is a complex, integrated process involving people, procedures, ideas, devices and organization for analyzing problems and devising, implementing, evaluating and managing solutions to those problems involved in all aspects of human learning” (Association for Educational Communications and Technology [AECT], 1977, p. 1).

The AECT 1994 definition of the field of instructional technology has been the most commonly used definition and is the first usage of the term instructional technology in defining the field. “Instructional technology is the theory and practice of design, development, utilization, management and evaluation of processes and resources for learning” (Seels & Richey, 1994, p.9). The 1994 instructional technology definition links theory and practice through functions performed by instructional technology specialists within the domains of designing, developing, utilizing, managing and evaluating (Seels, 1995).

More recently, the definition has been updated by the AECT in 2007 to replace instructional technology once again with educational technology. The new definition states that “educational technology is the study and ethical practice of facilitating learning and improving performance by creating, using, and managing appropriate technological processes and resources” (Association for Educational Communications and Technology [AECT], 2007, p1). Though the change from instructional technology to educational technology is obvious, there is also a change in purpose from the function of the tool to the ethical practice of facilitating learning and improving performance. The AECT 2007 definition of improving performance and facilitating learning shows the shift away from evaluating the tool to studying the way it is used to improve student learning and achievement. Educational technology and instructional technology were considered synonymous terms in the AECT 1994 publication and, in the AECT 2007 publication, they were also synonymous terms and considered elements of performance technology (Seels & Richey, 1994; AECT, 2007). This study is evaluating instructional tool utilization in an online environment and will use the term instructional technology from this point forward.

Online Learning and Instructional Technology

Online learning requires a technological device such as a computer, a tablet, and/or mobile phone to access the learning environment. Cuban (2001) stated that computer technology being added to the classroom was underused and had yet to return the gains in student achievement that were promised. Technology deployment in schools has three assumptions as outlined by Cuban (2001): increased technology availability would lead to increased use, increased use would lead to improvements in teaching practice, making instruction more effective, and improved teaching and learning would lead to student achievement. The increased use assumption appears to be true, because there is more technology being used in classrooms. But the assumption of technology making instruction more effective and improving teaching and learning still appears to need research into effective technology use within online environments (Lack, 2013; Tally, 2012; U.S Department of Education, 2010).

The assumption of increased use outlined by Cuban (2001) is required for online learning courses, which makes the investment necessary, but determining the investments' impact on student learning and achievement continues to be a research need (Cuban, 2001; Lack, 2013; Tally, 2012; U.S. Department of Education, 2010). Within an online learning environment, the tools being used can have an effect on student achievement if used effectively (Tally, 2012). The U.S. Department of Education (2010) meta-analysis of research found that few rigorous research studies of the effectiveness of online learning for K-12 students have been published. The study by Lack (2013) remarked that their literature review of online learning supported the idea that there have been few rigorous efforts to produce compelling evidence of the learning outcomes associated with online courses at the postsecondary level. Research that compares online courses to traditional face-to-face courses assesses a wide variety of outcomes and has yielded little, if any, evidence to suggest that online learning is more or less effective than face-to-face learning (Parker, 2015). According to the U.S. Department of Education in its 2010 meta-analysis, a great majority of estimated effect sizes are for undergraduate and older students, not elementary or secondary learners, and "without new random assignment or controlled quasi-experimental studies of the effects of online learning options for K–12 students, policy-makers will lack scientific evidence of the effectiveness of these emerging alternatives to face-to-face instruction" (p. xviii). If the learning environments are not producing different learning outcomes, then perhaps the level of student engagement in an online environment affects learning outcomes (Davidson-Shivers, 2009; Thurmond, 2003; Trowler, 2010).

Student Engagement and Interaction

The study by Trowler (2010) defined student engagement as being "concerned with the interaction between the time, effort and other relevant resources invested by both students and their institutions intended to optimize the student experience and enhance the learning outcomes and development of students and the performance, and reputation of the institution" (p. 3). The interaction between time, effort and resources invested by an institution would include the instructional technology needed to support learning both online and in the traditional classroom.

To better understand an interaction and its relationship with engagement and technology, it must first be defined. The study by Thurmond (2003) was not able to find a consensual definition for interaction in educational literature and developed the following definition:

> The learner's engagement with the course content, other learners, the instructor, and the technological medium used in the course. True interactions with other learners, the instructor, and the technology results in a reciprocal exchange of information. The exchange of information is intended to enhance knowledge development in the learning environment. (p. 4)

Thurmond's (2003) definition will be used to define interaction in this study as well. Based on the definition of interaction, the interaction between students, instructors, and the instructional technology would also need to enhance student learning and achievement. To determine which interactive engagements enhance student learning, there must first be an understanding of which characteristics of student learning are most effective in the classroom. Student learning was found to be most effective when the fundamental characteristics of active engagement, frequent interaction, and feedback were present (Harden & Laidlaw, 2013; Phillips, 2005; Roschelle et al., 2000; Sherman & Kurshan, 2005). Engagement is considered active when instructors use active learning techniques to engage students and improve learning (Van Amburgh et al., 2007). Active engagement/learning, frequent interaction with instructor and students, and frequent feedback are also supported by SPGP Principles 1, 2, 3, and 4. The frequency of interaction can occur with other students, instructors, or with the content in the course.

Interaction is a form of student engagement and, in distance/online education there are three types: learner-content, learner-instructor, and learner-learner (Moore, 1989). The types of interactions were labeled by Moore (1989) in an effort to create agreement among distance educators on the distinctions between the three types. While the distinction has been accepted by distance educators, the label is sometimes modified to include "student" instead of "learner." The "instructor" term is also sometimes replaced with "teacher" or "faculty." These modifications of the term are considered synonymous as the distinction between the three types remains consistent. This study will use the labels created by Moore (1989) in all cases except for references to the Seven Principles for Good Practice, which were developed before the types of interactions were identified by Moore, and will use the terms "student" and "faculty" (Chickering & Gamson, 1987).

In online learning environments, interaction is often viewed as necessary for student satisfaction and learning to occur (Davidson-Shivers, 2009; Weiner, 2003). With student learning and achievement in mind, a meta-analysis found that the effect size for achievement outcomes favored more interaction over less interaction (Bernard et al., 2009). All three interaction types of learner-learner, learner-instructor, and learner-content were found to have average effect sizes that were both significant and heterogeneous (Bernard et al., 2009). The interactions' heterogeneity supports Moore's (1989) distinction between the three types of interactions. Strengthening the learner-content interaction suggests that when students are provided strong course design features to help them engage in the content, it makes a substantial difference in terms of achievement (Bernard et al., 2009). Learner-instructor is also considered an element critical to the success of the instruction (Appana, 2008; Davidson-Shivers, 2009; Thurmond & Wambach, 2004). Learner-learner interactions have also been shown to help students develop metacognitive and self-evaluation skills (Jin, 2005). Student engagement through interactions has shown that more interaction affects achievement, but an instrument is needed to measure the level of engagement and interaction.

Measuring Student Engagement

The National Survey of Student Engagement (NSSE) organization developed an instrument designed to measure student engagement by using Chickering & Gamson's Seven Principles for Good Practice (Kuh, 2003a). Emphasizing good educational practices helps focus faculty, staff, and students on engagement in the tasks and activities that drive student learning outcomes (Kuh, 2003a). The use of Chickering and Gamson's SPGP for the NSSE instrument design allows the collection of data that can be pedagogically supported. The NSSE instrument even has an engagement indicator, specifically based on SPGP Principle 1, labeled student-faculty interaction. Other instruments such as the Classroom Survey of Student Engagement (CLASSE) and the Student Course Engagement Questionnaire (SCEQ) are measures of student engagement like the NSSE and rely on student self-reported data (Dixson, 2010; Handelsman, Briggs, Sullivan, & Towler, 2005). The study by Kuh (2001) explains that student self-reported data is likely to be valid if certain conditions are met and that student reports are the only feasible and cost-effective source of this kind of information. The study by Kuh (2001) further explains that it would be prohibitively expensive and probably logistically impossible to observe directly how students use their time and the extent of interaction.

The NSSE, which based the benchmarks for engagement on Chickering and Gamson's SPGP, has been mostly applied to post-secondary institutions and traditional classrooms (Campbell & Cabrera, 2011; Pascarella et al., 2008). The questions present in the NSSE were designed for the traditional classroom in 2000 and were revised in 2013 to include new measures and a student demographic indicator for online education status (National Survey for Student Engagement, 2013). Even with the new demographic indicator, it would be difficult to conclude that the NSSE would be a valid and reliable instrument to evaluate online secondary courses

(Bowman, 2010; Campbell & Cabrera, 2011; Pascarella et al., 2008). When evaluating student learning, it was found that self-reported data through course evaluations were not consistent with learning behaviors and that the lack of direct observation compounded the inconsistency (Bowman, 2010; Hung et al., 2012). Comparing self-reported and objective measures shows that student perception data when used solely to inform strategic decisions can result in a misrepresentation of the data and flaws in decision making (Bowman, 2010; Ferdig, 2006; Hung et al., 2012; Islam, 2016). Using self-reported data due to the cost and time limitations needed for more objective measures is no longer the only option available to researchers. Described later in this literature review, various instructional technology systems have been developed that can directly and objectively measure interaction and engagement factors that previously would have been cost-prohibitive for human observation.

Student Engagement and Student Learning

Two components of student engagement were time and effort. The study by Kuh (2003a) found that the more students study a subject, the more they learn about it, which relates to the student engagement component of time spent. The study by Coates, James, and Baldwin (2005) explains that effort involves both quality and quantity. The study by Kuh (2003b) also adds to the concept of effort and states that "the more students practice and get feedback on their writing, analyzing, and problem solving, the more adept they become" (p. 25). The study by Kuh (2009) explained that adeptness through engagement must continue to be studied against traditionally reported measures of student learning and achievement (Kuh, 2009).

An early study using the NSSE survey found some positive links between student engagement and ACT Collegiate Assessment of Academic Proficiency scores, but they were only modestly statistically significant (Ewell, 2002). A similar study by Hughes and Pace (2003) using NSSE results and college grade point average (GPA) for academic performance showed positive relationships. The study by Carini, Kuh, and Klein (2006) used the NSSE to corroborate what many other researchers have found, that student engagement is linked positively to desirable learning outcomes such as grades. While the NSSE is used by 1,400 colleges and universities, it does have some issues in terms of reliability and validity (Campbell & Cabrera, 2011; Porter, 2010). The NSSE is a self-reported measure of engagement and has not been applied to individual course measures of student learning and achievement (Pascarella et al., 2008). The study by Bowman (2010) found that self-reported measures did not accurately reflect longitudinal learning and that errors in student judgment and bias can inaccurately affect the results and subsequent decision-making. Due to the limitations of self-reported measures, an objective measure of frequency of tool use will be used to measure interaction and engagement for this study.

Frequency of Interaction

Student learning was found to be most effective when the fundamental characteristics of active engagement/learning, frequent interaction, and feedback were present (Van Amburgh et al., 2007; Harden & Laidlaw, 2013; Phillips, 2005; Roschelle et al., 2000; Sherman & Kurshan, 2005). The student learning characteristic of frequent interaction can be objectively measured through the frequency of occurrence within a course. In a traditional classroom, the quantity or frequency of interactive events is supported by Kuh's (2003b) statement that "the more students practice and get feedback on their writing, analyzing, and problem solving, the more adept they become" (p. 25). It is worth noting that the study by Kuh (2003b) did not look at the quality of the interactions, but instead used the frequency of responses to specific questions on the National Survey of Student Engagement (NSSE). The NSSE uses questions based on the SPGP to evaluate student and staff responses in terms of tasks and activities that drive student learning outcomes. The Martinez and Martinez (1992) study used a 2x2 experimental study to assess the final grade impact of experienced instructors and the frequency of assessments. The experimental group received three tests per chapter. The final grades in a course were shown to be affected by the frequency of assessments in a traditional classroom (Martinez & Martinez, 1992). A large-scale study of 2000 biology students taught by the same instructor in a traditional higher education classroom showed that frequent testing had a beneficial effect on student achievement (Khalaf & Hanna, 1992). The beneficial effect needs to be further defined, and other instructional tools besides assessments contribute to the benefit.

Proponents of frequent testing cite the advantages of frequent testing, including longer retention of material, preparation for high-stakes testing, extrinsic motivation, student preparation on tests, smaller amounts of materials for deeper processing, more classroom discussion, reduced test anxiety, useful feedback for the school on student performance, and increased classroom attendance (Gholami & Moghaddam, 2013). While the advantages may differ among researchers, Gocmen (2003) conducted a meta-analysis of 78 studies in a traditional face-to-face environment and determined that frequent testing was beneficial to student learning and academic achievement. According to the study by Gocmen (2003), the variation among the effect sizes could not be explained by the school level, whether secondary school or college level, and remains unknown. While the school level could not be determined, the study by Gocmen (2003) also reviewed curricular subject area, and, while the effect sizes were not found to be significant, social sciences accounted for the majority of studies and had the largest mean effect size. Curricular subject area may have an effect on student achievement and should be evaluated with other interactive events. It should be noted that the 78 studies analyzed by

Gocmen (2003) were from traditional education and focused primarily on formative assessments. There currently exists a need to extend this research to new educational environments such as online learning, and the research other interactive events beyond assessments.

If the frequency and immediacy of student interactions was increased, there was also increased learning as reflected by test performance, grades, and student satisfaction (Casem, 2006; Jung, Choi, Lim, & Leem, 2002; Picciano, 2002; Zirkin & Sumler, 1995). The study by Lundberg and Schreiner (2004) through a self-reported measure also found that frequent interaction with instructors was a strong contributor to student learning in a traditional post-secondary environment. In online education it was also found that the relative magnitude of interaction was a predictor of student achievement (Bernard et al., 2009; Hawkins, 2011; Lou, Bernard, & Abrami, 2006). It was also noted that the studies in the Bernard et al. (2009) meta-analysis of distance education rarely measured the actual amount of interaction (Borokhovski et al., 2012). An online wiki tool for collaboration was specifically studied by Farmer (2009), and the frequency of interaction with the tool was shown to be a significant predictor of enhanced knowledge. This study is designed to specifically measure the amount of interaction in the form of frequency of tool use and will be evaluating more than one tool to account for the three interaction types of learner-learner, learner-instructor, and learner-content. The types of instructional tools provided depend on the instructional technology system provided by the institution.

Feedback

While there is not an agreed-upon definition of feedback, is it best defined as information about the gap between actual performance of the student and the reference performance set by the instructor (Ramaprasad, 1983; Scott, 2014). Chickering and Gamson's

(1987) Principle 4 is focused on giving prompt feedback in order to improve teaching and learning. Students require timely and appropriate feedback on their performance to assess their own knowledge and competence (Chickering & Gamson, 1987). Student learning was found to be most effective when the fundamental characteristics of active engagement/learning, frequent interaction, and feedback were present (Van Amburgh et al., 2007; Harden & Laidlaw, 2013; Phillips, 2005; Roschelle et al., 2000; Sherman & Kurshan, 2005). The presence of feedback can be provided by instructors, other learners, and course content (Phillips, 2005). The way the feedback is delivered can vary, but the source of the feedback will involve students interacting with the course content, the instructor of the course, the other learners enrolled in the course, or a combination of the sources.

In an asynchronous online course, there are limited opportunities to provide students with face-to-face feedback, which requires instructors to use new approaches for providing feedback in an online setting (Bonnel & Boehm, 2011). The study by Bonnel and Boehm (2011) found that online instructors using the best available tools optimized the feedback provided to students. The category of using the best available tools had the following themes: maximize the technology, use rubrics, use templates, and use automated responses. Instructors can maximize their use of technology to provide feedback through announcement/updates, discussion boards, comments on graded work, grade received, and rubrics (Chickering & Gamson, 1987; Bonnel & Boehm, 2011; Phillips, 2005; Popkess, 2010).

The study by Pyke (2007) recorded all feedback interactions between students and instructors in an online course and found four methods of communicating: asynchronous posts, electronic chats, email messages, and graded assignments. Assignments were the most frequently used form of feedback and accounted for about 67 percent of the feedback given in the course overall (Pyke, 2007). Assignments were individual projects that were completed by students and uploaded to the instructor (Pyke, 2007). Graded assignments require an instructor to provide feedback through comments, annotations, and points earned. Other learners enrolled in the course can also provide feedback through peer review and group discussions (Chickering & Gamson, 1987; Bonnel & Boehm, 2011; Phillips, 2005; Popkess, 2010). The content of the course can also provide timely feedback through automated responses (Bonnel & Boehm, 2011). The automatic responses would need to be developed by instructors in advance, but assessments such as tests can provide instant feedback (Lai & Savage, 2013). The immediate feedback allows students to self-assess their gaps in knowledge by precise correct/incorrect responses and impartial feedback that explains why an answer is correct or incorrect (Ibabe & Jauregizar, 2010). Using a variety of sources for feedback creates a feedback-rich environment (Bonnel & Boehm, 2011). The variety of sources for feedback depends on the instructional tools provided by the instructor's institution. An instructional technology should be selected for pedagogical reasons, and Morgan (2003) determined that one of the reasons for using an LMS was to provide feedback to students.

Instructional Technology Systems - LMS, LCMS, and CMS

The AECT (2007) instructional technology definition includes appropriate technological processes and resources. In online learning the processes and resources can be combined to create an instructional technology system that controls all aspects of the learning process (Forouzesh & Darvish, 2012). The most common technologies used to deliver instruction over the Internet include: learning management system (LMS), learning content management system (LCMS), and course management system (CMS). An LMS will include the basic tools that allow for communication, collaboration, content delivery, and assessment. An LMS is different from a LCMS. An LCMS is used primarily for the development, maintenance, and storage of instructional content. An LCMS can deliver content, but it is usually missing the course administrative functions of an LMS. These differences will typically allow an instructional designer to build interactive web-based content into an LCMS, which would then be delivered to students within an LMS course (Ninoriya et al., 2011).

A CMS focuses on managing student enrollment and student performance and creating and distributing course content. This term is often used interchangeably with an LMS, but they are not exactly the same. A CMS has built-in content-authoring tools and can deliver content, but an LMS is often more robust in the content types it can deliver and contains additional reporting to assist instructors in improving student performance. When implementing a learning strategy, an LMS is the best option. When developing learning content, an LCMS would be the more appropriate choice (Guirgiu et al., 2014; Ninoriya et al., 2011). The acronym CMS also causes some confusion among researchers since it is also used to describe a content management system, which has components similar to an LCMS but focuses on the storage of the individual files used to create the learning content (Guirgiu et al., 2014). Systems such as Moodle and Blackboard that were originally known as a CMS have begun using LMS to describe their product (Forouzesh & Darvish, 2012; Muhsen et al., 2013).

Learning systems continue to evolve and future systems will likely create new terms to describe them as they evolve. While the CMS and LCMS have their place in online education, the LMS is the most commonly used and is a critical component for developing an online learning environment (Park, 2014). The online secondary school population selected for this study received its instruction through an LMS. The LMS provides an environment and location for learner-learner, learner-instructor, and learner-content interactions to occur (Goosen & van

Heerden, 2015). In terms of evaluating the frequency of interaction, research has shown that learning management systems may play a role in activating interactive behaviors (Bernard et al., 2009; Cechinel, 2014; Coates et al., 2005; Goosen & van Heerden, 2015; Hashim et al., 2011).

Evaluating Pedagogical Elements in an LMS

It is important to understand the pedagogical elements contained within an LMS because student interactions can be seen as part of the LMS infrastructure of the school and not as individual elements that add value to student learning (Coates et al., 2005). The study by Bongey (2012) explored whether an LMS could deliver Universal Design for Learning (UDL) using a control course that was lacking UDL elements and a treatment course that was UDL-compliant. The same LMS was used for both courses and "the very attributes that make the electronic LMS such a promising system for organizing and design UDL approaches may have concurrently diminished the strength of the research design itself and perhaps even its ability to yield a demonstrably positive result" (Bongey, 2012, p. 97). The statement of diminished strength of research design is important because it identifies that a strong pedagogical tool such as an LMS can make it difficult to evaluate different instructional approaches. Coates, James, and Baldwin (2005) would agree that an LMS is not a pedagogically neutral technology and, through its very design, can influence and guide teaching. The use of an LMS would then have pedagogical influence on the design of instruction, but the effects or influence are not well-defined or known (Bongey, 2012; Coates et al., 2005).

Chickering and Gamson's Seven Principles for Good Practice transfer well to an online environment (Chickering & Ehrmann, 1996; Dreon, 2013; Graham et al., 2001; Guidera, 2004; Lai & Savage, 2013). The SPGP were initially designed for traditional face-to-face instruction but, when used in an online environment, the classroom has changed from a physical space to a virtual space contained within an LMS. Just as a classroom is a pedagogically designed space, the LMS has also been pedagogically designed through the instructional tools provided for instructors (Coates et al., 2005). The following sections will detail the literature support for each of the LMS tools' connection to the pedagogical framework of Chickering and Gamson's Seven Principles for Good Practice.

Learning Management System Tools

The features of an LMS can vary between vendors and it can help to group the general tools offered for administrative and pedagogical functions. The sophistication and potential of each tool within the LMS can vary but can be generally categorized. The study by Coates, James, and Baldwin (2005) examined the effects of learning management systems on teaching and learning and created a four-part structure (pp. 20-21):

- asynchronous and synchronous communication (*announcement areas, e-mail, chat, list servers, instant messaging and discussion forums*)
- content development and delivery (*learning resources, development of learning object repositories and links to internet resources*)
- formative and summative assessment (*submission, multiple-choice testing, collaborative work and feedbac*k)
- class and user management (*registering, enrolling, displaying timetables, managing student activities and electronic office hours*)

The tools identified by Coates, James, and Baldwin (2005) are still available in current versions of learning management systems, but an LMS does not always contain all of the tools. An LMS may even have unique tools that are proprietary and limited to integrations with only a few learning management systems. But certain basic instructional tools exist within all learning management systems. These basic instructional tools are announcement/updates, assignment upload location, tests, discussion boards, web links, and pages. Using the basic LMS tools available in all systems allows this study to be more easily recreated and applied by researchers, regardless of the specific LMS provided by their institution. With one of the focuses of this study being student engagement and learning, each of the basic tools was evaluated for the presence of interaction and the measurement of the interaction.

The presence of an interaction and the ability to measure the interaction were used to evaluate each basic instructional tool for inclusion in the study. Pages and web links are considered course content and could be multimedia activities, static text content, embedded videos, textbook links, external websites, and/or images. This variability in what was provided through web links and pages would require a subjective measure to determine if active and engaged learning was taking place. In terms of measuring web links, the LMS did provide the number of times a web link was clicked, but did not specify unique clicks or whether each student clicked the web link. Content pages built within the LMS did not have any tracking information and it was not possible to determine if a student viewed the content on a page or amount of time spent on a page. Therefore evidence that all students viewed pages or clicked web links does not exist within the data stored in the LMS.

The inability to objectively confirm that active and engaged learning took place and the lack of measurement data removed the pages and web link tools from the study. The LMS tools of updates, assignments, tests, and discussion boards were present in all courses studied and the frequency of each occurrence exists within the LMS data. Student engagement and interaction research supported the inclusion of the LMS tools of updates, assignments, tests, and discussion boards (Bangert, 2004; Falakmasir & Habibi, 2010; Graham et al., 2001; Macfadyen & Dawson, 2010; Macfadyen & Dawson, 2012; McCuaig & Baldwin, 2012; Zafra & Ventura, 2009).

Because updates, assignments, tests, and discussion boards have shown they support student engagement through interaction and are objectively measurable, the LMS tools must also be evaluated for their pedagogical merits before inclusion in the study. The Seven Principles for Good Practice were found to be present in online instructional tools provided within an LMS (Dreon, 2013; Lai & Savage, 2013; Phillips, 2005; Ray, 2005; Woods, 2004). The LMS tools of focus for this study are those supported by literature as having a strong connection to Chickering and Gamson's Seven Principles for Good Practice. The following list is a summary of the connections and the following pedagogical support sections will provide more detailed support for each of the LMS tools.

- *Updates - SPGP 1 and 4*: SPGP Principle 1, which encourages contact between students and faculty, is most strongly supported by the LMS tool through time-delayed asynchronous communication (Chickering & Ehrmann, 1996; Ray, 2005). Students considered SPGP Principle 1 to be most successfully implemented by instructors in online courses (Crews et al., 2015). The study by Bonnel and Boehm (2011) found that instructors used the announcement/update tool to communicate feedback that was common to all students rather than answering them individually. The LMS structure of asynchronous and synchronous communication specifically lists updates as an LMS tool example (Coates et al., 2005).
- *Assignments- SPGP 1, 3, and 4*: SPGP Principle 3, active learning techniques, is most strongly supported by the LMS assignment tool and the concept of learning by doing (Chickering & Ehrmann, 1996; Dreon, 2013). SPGP Principle 4, giving prompt

feedback, is also supported in the LMS assignment tool (Chickering & Ehrmann, 1996). Electronically submitted assignments saved time for the instructors, which allowed them to provide more timely feedback (Lai & Savage, 2013). SPGP Principle 1, encouraging contact between students and faculty, is supported by the LMS tool through time-delayed asynchronous grade feedback (Chickering & Ehrmann, 1996). The submission and feedback component of assignments is also specifically listed as an example of the LMS structure for formative and summative assessment (Coates et al., 2005).

- *Tests - SPGP 1, 3, and 4*: SPGP Principle 4, giving prompt feedback is most strongly supported in the LMS test tool (Chickering & Ehrmann, 1996). Tests can provide instant feedback to the student through the development of question level feedback for correct and incorrect answer responses (Lai & Savage, 2013; Ritter & Lemke, 2000). SPGP Principle 3, using active learning techniques, is also supported by students applying their learning through the LMS tests tool (Phillips, 2005; Vogt, 2016). SPGP Principle 1, encouraging contact between students and faculty, is supported by tests that contain essay responses that require asynchronous instructor grade feedback (Chickering & Ehrmann, 1996). The multiple-choice testing and feedback component of tests is also specifically listed as an example of the LMS structure for formative and summative assessment (Coates et al., 2005).
- *Discussion Board - SPGP 1, 2, 3, and 4*: SPGP Principle 2, developing reciprocity and cooperation among students, is most strongly supported in the LMS discussion board tool (Chickering & Ehrmann, 1996). SPGP Principle 3, active learning techniques, is also supported by the LMS discussion board tool through engaging learners in a collaborative process of building knowledge with instructors and other students (Dreon, 2013; Phillips,

2005). SPGP Principle 4, giving prompt feedback, is supported by the instructor and other students' contributions to the LMS discussion board tool (Thiele, 2003). SPGP Principle 1, encouraging contact between students and faculty, is supported by discussion boards through asynchronous replies to student posts and grade feedback (Chickering & Ehrmann, 1996). The LMS discussion board tool is specifically listed as an example of the LMS structure for asynchronous and synchronous communication and formative and summative assessment (Coates et al., 2005).

The LMS tool connections show that SGPG Principles 1, 2, 3, and 4 are supported by updates, assignments, tests, and discussion boards. SPGP Principle 1, encouraging contact between faculty and staff, was supported by all four LMS tools. SPGP Principle 3, active learning, was supported by the graded LMS tools of assignments, tests, and discussion boards. The SPGP Principle 4 of giving prompt feedback was also supported by the graded LMS tools of assignments, tests, and discussion boards. In their study, Chickering and Gamson (1987) stated that not all Seven Principles for Good Practice need to be present and can stand on their own, but that their effect multiplies when combined. Evidence supports that the Seven Principles for Good Practice enhance active learning and interaction which promotes engagement (Crews et al., 2015; Pascarella, 2006; Popkess, 2010; Thurmond & Wambach, 2004). SPGP Principles 1, 2, 3, and 4 and the fundamental characteristics of student learning share an emphasis on active learning, frequent interaction, and feedback. SPGP Principles 5, 6, and 7 would require an evaluation of the content provided through the LMS tools and are therefore considered outside the scope of this study measuring interaction events through the frequency of LMS tool use.

Greater attention is needed to aspects of curriculum organization, pedagogy, assessment, communication, support strategies, and resources that promote student engagement and learning in regard to the effectiveness of online delivery and the utilization of specific tools within the online environment (Brinthaupt, Fisher, Gardner, Raffo, & Woodard, 2011; Ehrmann, 1995; Hutchins, 2003; Tomas, Lasen, Field, & Skamp, 2015;). The focus of research should be on which teaching and learning strategies are best for your audience and which technology is best for supporting those strategies (Ehrmann, 1995). In 1996, a year after Ehrmanns study, Chickering and Ehrmann co-authored an article that explained how to implement the SPGP through instructional strategies with various technologies. In terms of online learning effectiveness, the technology used is less important than instructional strategies (Worley, 2000; Hutchins, 2003). Nevertheless, technology itself can offer rich pedagogical experiences to improve student learning by improving student engagement (Carle et al., 2009; Pemberton, Borrego, & Cohen, 2006). The following pedagogical support sections will explain each LMS tool and the instructional strategies they support, using the Seven Principles for Good Practice as a pedagogical framework.

Pedagogical Support for the LMS Update Tool

Updates from their instructor will usually be the first interaction students have when entering the LMS to view their course. Some systems may even email a copy of an update to the student. Updates can be used to inform students of due dates, clarification of assignments, new assignments, or other relevant class information. Previous studies have shown that within an LMS, the update tool is used by instructors to gain the attention of students and provide information (Carmean & Haefner, 2002; Lonn, 2009; Ssekakubo, Suleman, & Marsden, 2013; Malikowski, Thompson, & Theis, 2007). An update is a synonymous term for an announcement, and different learning management systems label the function as either an update or an announcement. The LMS in this study labels the communication function as an update. Updates are an interaction in the form of learner-instructor engagement (Graham et al., 2001). The study by Lonn (2009) defined a basic interaction as any kind of communication that takes place online within an LMS tool. Lonn's (2009) study considered updates a basic interaction and further distinguished updates from collaboration due to students' not being required to develop and/or sustain shared ideas about a collective problem. This study will also consider updates a basic interaction that is measured through the frequency of updates created and is not evaluating the collaboration between students and instructor.

Chickering and Gamson's Seven Principles for Good Practice (SPGP) are present in the LMS update/announcement tool in the first principle of encouraging contacts between students and faculty. The updates/announcements were found to be a great strength of the LMS and the main source of public learner-instructor interaction (Graham et al., 2001). The study by Bangert (2004) used an LMS with announcement tools and identified the SPGP of student-faculty contact as a critical factor in motivating performance.

Pedagogical Support for the LMS Assignment Tool

Macfadyen and Dawson (2010) studied the number of completed assignments and loosely tied assignments to the pedagogical framework of Chickering and Gamson's SPGP. The assignments had the SPGP of encouraging interaction, promoting active learning, providing prompt and detailed feedback, and time on task (Harrington, 2011). While assignments were a significant contributor to final grades, the time on task was not an accurate reflection due to offline writing and research that was not tracked in the LMS and the exclusion of assignments from their study (Macfadyen & Dawson, 2010). While Macfadyen and Dawson excluded assignments from their study, the McCuaig and Baldwin (2012) study included assignments because they were the largest part of independent work in the course. The McCuaig and

Baldwin study did not include the frequency of assignments in the course but instead used the number of times the assignment was viewed. The number of views of the assignment was not found to be significantly correlated to the final grade (McCuaig & Baldwin, 2012; Falakmasir & Habibi, 2010). The number of assignments completed by the student was studied by Zafra and Ventura in 2009. Their study also included the total time spent on assignments. The study by Zafra and Ventura (2009) did conclude that completing a certain number of activities would result in passing the course, but the study also had seven different courses with assignment frequency between 0 and 19. The assignments were also optional, and Zafra and Ventura (2009) noted in their study that some students completed none of the assignments and others completed all of them. Zafra and Ventura (2009) noted that there is a need for a study that does not allow optional completions and looks specifically at the activities and their predictive power for a final grade instead of just passing marks. Falakmasir and Habibi (2010) were also interested in the pedagogical links to assignments and stated that their Moodle LMS followed Social Constructivism learning styles. Social Constructivism has components of Chickering and Gamson's SPGP, specifically encouraging interaction with students and faculty and providing timely feedback (Keaton & Bodie, 2011).

Pedagogical Support for the LMS Test Tool

Tests provide students with an interaction point of assessing their knowledge of the content. The tests can be ungraded or graded. The test design can be entirely auto-graded with automatic question feedback, partially auto-graded with instructor grading, or entirely instructor-graded. Instructor-graded question types are essay or short-answer. If a test does not contain any essay or short-answer items, it will automatically provide the student with the grade upon completion. Chickering and Gamson's SPGP Principle 4 of giving prompt feedback is achieved by tests, especially auto-graded tests, due to immediate feedback. The study by Martin and Klein (2008) looked directly at the SPGP concept of practice with feedback by designing test questions into their multimedia instruction.

Knowing if the test is graded or ungraded is important when conducting research studies because ungraded optional self-assessments have been found to have less participation by students (Macfadyen & Dawson, 2010; McCuaig & Baldwin, 2012). The number of ungraded self-assessment completions were found to be a significant predictor of final grades (Macfadyen & Dawson, 2010; McCuaig & Baldwin, 2012), but there is a potential bias of students completing optional ungraded work versus students who skip the assessment. To remove this bias, a study would need to use tests that are completed by all students in the course.

In their 2009 study of the time spent on tests and the pass-or-fail frequency, Zafra and Ventura concluded that the most relevant activity was passing the tests, because they required less time and fewer completions to get a passing grade for the course. There was not a conclusion about whether the time spent on tests was significant in achieving a passing score. Their research did have some limitations, due to the fact that only four of the seven courses studied had tests built into the course and the frequency of tests ranged from 6 to 31 (Zafra & Ventura, 2009). The study by Macfadyen and Dawson (2010) also showed that time spent online correlated only weakly with student final grades and was not a significant predictor. The time spent for each activity has also been considered an inconsistent measure, since time spent doesn't necessarily mean active work and time spent on online activities is not significantly correlated with student achievement (Bowman, Gulacar, & King, 2014; Farmer, 2009; Macfadyen & Dawson, 2010; Weinberg, 2007). Research has shown that frequency of assessment does have an impact on final grades, but not time spent on the assessment (Bowman et al, 2014; Farmer, 2009; Macfadyen & Dawson, 2010; McCuaig & Baldwin, 2012; Weinberg, 2007; Zafra & Ventura, 2009). Therefore, the time spent on assessments is less important than the frequency of tests in determining student learning and achievement.

Pedagogical Support for the LMS Discussion Board Tool

Discussion boards are the forum for peer-to-peer interaction within an LMS and help facilitate the learning process (Macfadyen & Dawson, 2012). The learning process of discussion boards is Chickering and Gamson's SPGP Principle 2 of developing reciprocity among students. A survey about LMS usage conducted by Harrington in 2011 tied the SPGP to each survey element, and discussion boards were brought up as the most common way to encourage student interaction and develop reciprocity and cooperation among students. The interaction, as defined by Lonn (2009), is any kind of communication that takes place online within an LMS tool. Lonn (2009) also further explained that discussion boards can be accessed and read by all students and this interaction can be studied.

The number of discussion boards present in a course is not as prevalent in research as the evaluation of student responses within a discussion board. Abdous, He, and Yen (2012) studied the discussion board posts by students to create response themes that were then correlated to final grades. The interaction with the instructor related to questions on learning/comprehension was shown to have the highest number of final grades in the A to A- range (Abdous et al., 2012). The total number of discussion board messages posted by students was also studied by Macfadyen and Dawson in 2010. Their study concluded that student engagement with peers is an important indicator of success and was their most significant predictive variable for final grades (Macfadyen & Dawson, 2010). The studies were not specifically focused on the number of posts but more on the ability of a discussion board to provide interaction with students and the instructor (Abdous et al., 2012; Macfadyen & Dawson, 2010). The presence of a discussion board would provide an interaction point with instructors and students and, if graded, would also provide feedback to the student. Measuring the frequency and quality of student posts would require student data that are outside the scope of this study and a qualitative instrument to determine quality of interactions. Therefore, the objective measure of the frequency of discussion boards present within the course will be used for analysis in this study.

Student Achievement and Student Learning

The National Board for Professional Teaching Standards (NBPTS) in 2011 defined student achievement as "the *status* of subject-matter knowledge, understanding, and skills at one point in time." Student learning, on the other hand, is "the *growth* in subject-matter knowledge, understanding and skills over time" (National Board for Professional Teaching Standards, Linn, Bond, Carr, Darling-Hammond, Harris, Hess, & Shulman, 2011). The distinction between achievement and learning is important in this study. For this study, student achievement will be measured by the final grade score at a specific point in time, which will be the end of the semester. Student learning is about growth over time, which will be measured in this study at the beginning and end of the course through pretest and posttest scores.

For course-level measurements, student final grades have been shown to be a good indicator of student achievement for the course. Final grades show the performance achieved at the end of the course but do not account for the student's prior knowledge or inherent academic capabilities (Delucchi, 2014). A pretest is a direct measurement of knowledge at the beginning of a course and a posttest is a direct assessment of the knowledge at the end of a course. The difference in the scores is attributed to the learning that occurs over the duration of the course. Pretest and posttests have been shown to be a good indicator of student learning growth

(Delucchi, 2014). For final grades, the quantity of interaction with course activities was found to be predictive, the more activity, the higher the performance (Basol & Johanson, 2009; Gholami & Moghaddam, 2013; Gibbs, 2003; Kuh, 2003a; Peterson & Siadat, 2009; Wang & Newlin, 2000).

Educational Data Mining and Learning Analytics

Data mining can be applied to data coming from both traditional classrooms and online classrooms, but the data mining techniques will differ based on the data sources and techniques (Romero & Ventura, 2007). In online environments, Educational Data Mining (EDM) collects direct measures through LMS logs, database queries, and analytics. LMS systems contain large logs of data on the student's activities within the online environment (Romero & Ventura, 2007). The usage information can then be extracted and analyzed to provide visual information that tracks student behavior and access. This action would be considered learner-content interaction, as it is tracking access and time spent in online content areas. The data mining methods applied to the data tend to use clustering and pattern recognition to associate students with various groups (Romero & Ventura, 2007). Clustering students into groups puts the focus on the user or group they are associated with when looking at predictive analyses using learning outcomes such as final grades. The study by Ueno (2006) used Bayesian predictive distribution on outliers that used irregular learning patterns, but it was limited to a small sample and focused on time spent on each item. User modeling and profiling can be used in real-time adaptations, but some applications of data mining are more experimental (U.S. Department of Education, Office of Educational Technology, 2012). Experimental data mining actions are best suited to instructional improvement. According to the U.S. Department of Education's Office of Educational Technology report in 2012, K-12 schools and districts are starting to adopt analyses for detecting areas of instructional improvement, setting policies, and measuring results. Administrative data and classroom-level data are normally contained in separate systems and present a difficult challenge, but the potential to make visible the data that previously would have been unseen, unnoticed, and unactionable (U.S. Department of Education, Office of Educational Technology, 2012). In terms of research needs, the U.S Department of Education Office of Educational Technology (2012) encouraged two main areas of focus:

1. Continue to research methods for using identified student information where it will help most, anonymizing data when required, and understanding how to align data across different systems.
2. Understand how to repurpose predictive models developed in one context to another.

Aligning data and predictive models with high degrees of validity is one form of EDM. Prediction models can be used to study which specific constructs play an important role in predicting another construct (Siemens & Baker, 2012). Evaluating the constructs that have the most impact on student learning and achievement is needed to increase the validity of predictive models. Using EDM, researchers could build models to answer such questions as "What features of an online learning environment lead to better learning?" (U.S. Department of Education, Office of Educational Technology, 2012). The need to answer the question of "features" in online learning is being evaluated in this study. The features are described as the LMS tools of updates, assignments, tests, and discussion boards.

EDM and learning analytics share a common trait of measuring and collecting data, but each has a different emphasis. EDM emphasizes system-generated and automated responses to develop new methods for data analysis. Learning analytics are the application of known methods that would enable human tailoring of responses (Johnson et al., 2011). The key application of learning analytics is to monitor and predict student learning performance. The frequency of LMS tools contained within a course is not currently a system-generated response provided to instructors of online courses and requires EDM. Using EDM, instructors can evaluate the structure of their course content and its effectiveness toward student learning (Romero et al., 2008). Using EDM, the frequency of LMS tool use will be extracted from the LMS data and evaluated. This study will use EDM methods to determine if the frequency of LMS tool use is a predictor of student learning and achievement. The data mining techniques will be used to create a new model focused on the frequency of LMS tool use by instructors. For the new EDM model to become a known learning analytic method for instructors to use for course modifications, more research using experimental design will be needed.

LMS Tools to Predict Student Learning and Achievement

Each of the LMS tools of updates, assignments, tests, and discussion boards has been shown to support student learning and achievement. The LMS tools are also supported by the pedagogical framework of Chickering and Gamson's Seven Principles for Good Practice. The use of LMS tools assists the application of SPGP Principles 1, 2, 3, and 4 in an online learning environment. SPGP Principles 5, 6, and 7 emphasizing time on task, communicating high expectations, and respecting diverse talents and ways of learning are implemented in online environments (Crews et al., 2015; Graham et al., 2001; Woods, 2004). But SPGP Principles 5, 6, and 7 would require the researcher to evaluate the content that is provided by the instructor and determine whether it emphasizes time on task, communicates high expectations, and/or respects diverse talents and ways of learning, which is outside the scope of this study.

One of the limitations of previous research studies related to course-level activities is that many studies evaluated only one specific course within one specific higher education institution (Bowman et al., 2014; Macfadyen & Dawson, 2010; Weinberg, 2007; Wong, 2016). This makes it difficult to generalize findings to other subjects or other institutions. It is with this limitation in mind that this study was designed to evaluate courses across multiple subject areas with fully online secondary students. The study by Macfadyen and Dawson (2010) also showed that time spent online correlated only weakly with student final grades and was not a significant predictor. The time-spent for each activity has also been considered an inconsistent measure, since time spent doesn't necessarily mean active work and time spent on online activities is not significantly correlated with student achievement (Bowman et al., 2014; Farmer, 2009; Macfadyen & Dawson, 2010; Weinberg, 2007). The lack of accuracy for measuring time spent and non-significant correlation with student achievement supports the decision not to include time spent data for the LMS tools. Time spent data is also student-level data which is outside the scope of the course-level frequency of LMS tool data that is being evaluated in this study. The study by Macfadyen and Dawson (2010) concluded that pedagogically supported LMS tools should be evaluated to determine their applicability in an online classroom and that the frequency of use for the tools affects the predictability of student achievement as measured by final grades received in the course.

Student achievement will be measured by using the final grade received by students in the course. Student learning will be measured by pretest and posttest scores earned at the beginning and end of the course. The frequency of interactive engagements between student and instructor using the LMS tools of updates, assignments, tests, and discussion boards will be measured by the quantity present in each online 18-week or 36-week course. The frequency of the LMS tools will be analyzed using regression analyses to determine their predictive validity for student learning and achievement. The online secondary courses will also be categorized by subject area to determine if different frequencies of LMS tools within a curricular subject area have any effect on student learning and achievement. This information can be used by educators to improve and adapt the current online curriculum and evaluate the impact of the instructional changes on student learning and achievement. Based on this research, the methodology chapter details the research questions of this study.

CHAPTER III

Methodology

This study will investigate the predictive validity for the frequency of LMS tools used by instructors and the effect on student semester final grades and posttest scores. A hierarchical multiple regression will be used to determine if the variance is significant. The LMS tools of updates, assignments, tests, and discussion boards will be used in this study. The SPGP and characteristics of effective student learning related to active learning, frequent interaction, and feedback are present within the LMS tools. The study will also explore two factors that may have influence on the frequency of LMS tool use by instructors. The first factor, curricular subject area, will be added to both semester final grades and posttest predictive models. Curricular subject area will be added to the analysis after the frequency of LMS tool use variables and will be used to determine if curricular subject area significantly adds to the variance of the predictive model. The course length is a variable that only applies to posttest analysis. Posttests are completed at the end of year-long courses and would contain more than one semester of knowledge gained by students. The course length variable will be used to group year-long courses and semester-long courses for analysis.

The pre-existing data will be gathered from the LMS, student information system (SIS) databases, and Virtual High School (VHS) pretest/posttest Excel workbook. The data will be gathered for VHS enrollments from school year 2014-2015 and school year 2015-2016. The two schools years account for roughly 7,000 enrollments in VHS courses. The courses are asynchronous and taught by certified secondary school teachers. The course enrollment sizes can vary between 15 and 30 students per section of the course. The students, who are enrolled in traditional American high schools located around the world in eight different time zones, enroll in VHS courses to supplement the local offerings at their schools.

Organization and Virtual High School

The Department of Defense has established federally run schools to provide education for the children of military families stationed at various bases around the world. The schools were initially run and managed by the military branches they served but were later brought under a single umbrella federal agency. The civilian federal organization that was created is one of only two federally-operated school systems. The organization is responsible for planning, directing, coordinating, and managing pre-kindergarten through 12th grade educational programs. The organization provides education directly to military-connected children through a network of locally operated American diploma granting schools. The organization is globally positioned, operating 168 schools located in eleven foreign countries, seven states within the United States, Guam, and Puerto Rico. The schools located on military bases around the world are considered "local" schools and are staffed with civilian federal employees who provide an American high school experience. The organization has approximately 15,000 employees who serve more than 74,000 children of active duty military and DoD civilian families.

The local schools provide core curriculum and electives for grades Pre-K through 12. Due to staffing needs and minimum class size requirements, the local schools may not be able to offer a course the student wants or needs. To meet the needs of the local school students, the Virtual High School (VHS) was created in 2010 to offer online course options for secondary school students. VHS provides only secondary courses and accepts enrollments from the 46 local secondary schools. VHS, which does not currently offer online elementary or middle school courses, is committed to ensuring that all school-aged children of military families are provided a world-class education that prepares them for postsecondary education and/or career success and to be leading contributors in their communities as well as in our 21st century globalized society. Since 2010, VHS has been a school fully accredited by the AdvanceED North Central Association Commission on Accreditation and School Improvement (NCA CASI). The staff is comprised of administrators, counselors, special needs educators, instructional designers, educational technologists, instructors, and support. The three hubs, which are in the United States, Germany, and Japan, are in three locations to have staff available for synchronous communication to support a global organization. VHS offers 88 courses, including 52 year-long courses and 36 semester-long courses. A year-long course is 36 weeks in length and a semester-long course is 18 weeks. The courses are offered fully online, with asynchronous content through the LMS provided by the organization. For real-time synchronous communication, the instructors have the option of using third-party systems outside the LMS that include the Adobe Connect virtual classroom and an instant message chat system.

Population

The population selected for this study is secondary students taking online asynchronous courses who are enrolled in traditional American high schools located on U.S. military bases around the world. The secondary school population was selected based on the U.S. Department of Education's 2010 meta-analysis of K-12 research that found "few rigorous research studies into the effectiveness of online learning." In order to achieve a more heterogeneous population, the sample needed to include all 65 online asynchronous courses offered to all secondary school students. School year 2014-15 and school year 2015-16 enrollments came from a total of 86 secondary schools located in eight different time zones. The different time zones placed greater emphasis on the asynchronous course design and interaction points of the LMS tools, as face-to-face instruction provided to the entire class was difficult and in most cases not possible. The size of classes also mirrored the traditional education size of 20-40 students, which allowed the instructor more time to spend on individual feedback provided through the LMS tools.

Guidance for virtual school course selections is provided to students by counselors, instructors, and school support staff. The students enroll in virtual classes to supplement their current education or, in some cases, to take a course they would like that is not offered by the local school they attend. Virtual classes are not designed to replace the traditional brick-and-mortar school class but will sometimes receive enrollments if the local school exceeds its capacity to teach a specific subject. Student demographic data will include descriptive statistics for: grade level, gender, race, English language learner (ELL) status, and special education designation.

Data Sample

The data sample will use a purposive sampling technique that includes the total population sample of the organization. The study is designed to assess the LMS tools for the specific population of online secondary students. Because the data are pre-existing, it is possible to collect the data for the entire population at the organization. The data will include students' semester final grades, pretest/posttest scores, and demographics from school years 2014-2015 and 2015-2016. There will be approximately 7,000 student enrollments from both school years. The two years of data will be organized into one dataset. The course code will be used to identify curricular subject area and course length. The curricular subject area and course length will be manually added to the data sample by the researcher. The curricular subject area is based on the organization's categories of: career and technical education (CTE), fine arts, health and physical education (PE), English, math, science, social studies, and world languages. Course length will be listed as 18 weeks for semester-long courses and 36 weeks for year-long courses.

Student demographic information will be collected through the student information system (SIS) and will include designations for special education and English language learner (ELL). Students with special education needs at the organization can change the frequency of assignments, tests, and discussion boards provided in the course. Therefore, data associated with students with special education designation will be excluded from the study. The courses are only offered in English. English language learners will have additional barriers in learning the content. With these barriers in mind, students with English language learner designation will be excluded from this study. There is also an option for students to transfer into a virtual school course mid-semester. To determine transfer status, the field for "date student added" will be used to determine if the student should be classified as a transfer student. Students who transfer into the course with less than 50 percent of the semester remaining will be excluded from the study as they will not have the same frequency of LMS tool exposure as students who have been enrolled in the course since the beginning of the semester. Future research could compare and analyze the excluded populations using the design of this study.

Data Collection

This study is using only pre-existing data contained in the LMS, SIS, and VHS Excel workbook. The request for data will be sent to the Research and Evaluation Branch of the organization. The Research and Evaluation Branch will provide de-identified data to the researcher. The student ID, student name, instructor ID, and instructor name will not be included in any data sent to the researcher. The data will be formatted in an Excel workbook for import into statistical analysis software programs. The SIS data will contain course name, course ID, student semester final grades, and student demographic data. The student demographic data will include: grade level, gender, race, English language learner (ELL) status, and special education designation. The pretest and posttest score data are currently maintained by the VHS Educational Technologists in an Excel workbook. The data contain the following fields: school year, course name, course ID, student ID, pretest score, and posttest score. The Research and Evaluation Branch will request a copy of the pretest/posttest data from the VHS and will align the pretest/posttest student data to the SIS student demographics. The de-identified data sent to the researcher will include grade level, gender, race, ELL status, special education designation, course ID, semester final grades, pretest scores, and posttest scores. The demographic fields will allow descriptive statistics to be run for background information on the population. The demographic fields will also allow the researcher to exclude individual student data using ELL status and special education designations.

The frequency of updates, assignments, tests, and discussion boards will be collected by a request from the Research and Evaluation Branch to the LMS administrator to run a LMS database query using Application Programming Interface (API) fields. The query will be run by the LMS administrator at the organization. The query will be limited to the school ID for the VHS and will not include data for any of the other schools at the organization. The data table will organize the query results by course, which the query will extract from the Section School Code and Grading Periods. To measure the frequency of updates, only the timestamp field of last updated will be extracted. The timestamp will be in a Unix computer format and will require conversion to a human-readable time-date stamp by the researcher. To measure the frequency for assignments, tests, and discussion boards, the following fields will be extracted: title, grading period, grading category, published, type, dropbox submissions, and assignees. The assignee's field is an integer value that shows whether the content has been individually assigned to a certain number of students. If the assignee's field is "0," all students have access to the content. If the field is "1," then one student has been assigned the content and the other students cannot access it. The LMS fields are related to the course content. None of these fields includes identifiable information for students or instructors. To further limit identification, the information created by the instructor will not be included in the query or provided to the researcher. The LMS query will not contain any user data such as user ID, user name, or any user-identifiable information. The LMS tool frequency data will be provided to the Research and Evaluation Branch by the LMS administrator.

The Research and Evaluation Branch will provide two de-identified Excel workbook files to the researcher. Both workbooks will have the data organized by course ID. The first data workbook will include student demographic data, semester final grades, pretest scores, and posttest scores. The second data workbook will include frequency of LMS tool use data. The course ID includes a code for curricular subject area. The curricular subject area field will be manually populated by the researcher, using the subject area code after receiving the de-identified data from the Research and Evaluation Branch.

Anonymity will be maintained as the researcher will never receive any data that contain any user-identifiable information. Consent will not be required by participants, as the data is pre-existing and de-identified. The researcher will not interact with any users outside the Research and Evaluation Branch at the organization and will not interact with any students. The de-identified data do not allow the researcher to identify students through the data provided. The Excel workbook and data analysis files will be provided to the researcher on 128 bit encrypted password-protected flash drives. In all instances, the researcher will take every effort to secure and protect the confidentiality of the data. When the flash drives are not in use, they will be locked in a fireproof safe at the researcher's home. A backup of the files will be copied to a second drive that will be stored in the same location to prevent lost data due to flash storage corruption. When the study is complete, the drives will be locked in the fireproof safe for a duration of five years. After five years, the drives will be removed and destroyed. No identifying information will be included in the data analyses or any publication of this research.

The LMS data are vast and complex, which requires EDM to collect, preprocess, apply data mining techniques, and interpret results. Data mining can be used when a moderate number of factors are involved that explore the data and confirm the hypothesis of the researcher (Romero et al., 2008). The fields in the LMS database query were selected based on the needs of this study. The raw data, once extracted required additional sorting and filtering to create a count of each item. The mined data can then be turned into knowledge that can be filtered for decision-making (Romero et al., 2008). This study is using EDM to build an analytic model to discover patterns and tendencies of instructor LMS tool use.

Variables

This study will be evaluating course-level frequency data that are not dependent on individual student completion data. All variables will be associated with each course by the unique course ID. Therefore, all variables will be associated with the course and not evaluate the individual grades the student earned for the LMS tools. The dependent variables of semester final grades and posttest scores represent a single course level value for each student. The pretest control variable is also a single course level value for each student. The frequency of each independent variable will be measured by semester for each course. The frequency of each LMS tool will be added to the student record. The independent variable of curricular subject area does not require any modifications to become a course-level measure. The following subsections will provide more details for each variable.

Dependent variables. The study uses semester final grades and posttest scores as the dependent variables. The pretest will be used as a control variable for prior knowledge in the semester final grade and posttest regression analyses.

- Semester Final Grade - The semester final grade is a continuous numeric percentage value. There is a system-wide grading scale that converts numeric final grades to letter grades for GPA calculation, but the score is reported to the SIS as a numeric value between 0 and 100. A semester grade is calculated one of two ways, at the discretion of the instructor. The semester final exam (SFE) in the course can be worth a weight of either 10 percent or 20 percent. The semester is broken down into two graded quarters, quarter 1 (Q1) and quarter 2 (Q2), which must be equally weighted. The formula to calculate semester final grade is Q1*weight+Q2*weight+SFE*weight = Semester Final Grade. Following is an example for a student who earns Q1=90%, Q2=84%, and SFE=95%, with the teacher selecting a 20% weight for SFE: 0.9*0.4+0.84*0.4+0.95*0.2 = 0.886, which is a semester final grade of 88.6 percent. The individual student percentages for semester final grade scores will be uniquely identified by the course code.
- Posttest Score - Instructors are responsible for creating the posttest for their course. The instructors were not provided any specific design guidance for the creation of the posttest. The posttest is ungraded, but some teachers may provide points for completing the posttest. There is not a time limit for completion and students cannot view their answers after they are submitted. The amount and type of questions included in the posttest vary by course. The total points possible for the posttest also vary by course. To account for

the variance in points possible, all scores will be normalized to a percentage scale. The individual student percentages for posttest scores will be uniquely identified by the course code.

Control variables. In order to control for prior knowledge, the pretest score will be used as the control variable for both dependent variables. The control variable will be used in Block 1 of the regression analysis. Courses that do not have any student data associated with pretest scores will be excluded from this study.

- Pretest Score - Instructors created the pretest for their course. The pretest is ungraded, but some teachers may provide points for completing the pretest. There is not a time limit for completion and students cannot view their answers after they are submitted. The amount and type of questions included in the pretest vary by course. The total points possible for the pretest also vary by course. All pretest scores are normalized to a percentage scale to account for point variance. The individual student percentages for pretest scores will be uniquely identified by the course code.

Independent variables. The independent variables were identified through the literature and the interaction points available within the LMS. Assignments, tests, and discussion boards have an additional designation for grading period. The grading periods are date ranges associated with each quarter and semester final exam. The grading periods, in chronological order, are Quarter 1, Quarter 2, Semester 1 Final Exam, Quarter 3, Quarter 4, and Semester 2 Final Exam. A semester includes two quarters and a final exam. The instructor of the course assigns a grading period to each assignment, test, and discussion board. The grading period will be used to measure frequency by identifying the occurrence of the interaction by semester.

Therefore, all interactions contained within the first grading period, second grading period, and semester exam grading period will be combined to provide a single value for frequency by semester.

The independent variable will be organized into two blocks for simultaneous entry during different phases of the hierarchical regression analysis. The independent variables are listed below, along with a description of the interaction event.

Block 2.

- Frequency of Updates (#UP) - The frequency will be measured by the number of updates created by the instructor. In a virtual class, updates are the main method to reach students and are considered a learner-instructor interaction event. This is the only non-graded frequency variable included in the study.
- Frequency of Assignments (#AS) - The frequency will be measured by the number of assignments created in the course. Assignments require an instructor for evaluation and are considered a learner-instructor interaction event. All assignments that have been assigned a grading period by the instructor will be included.
- Frequency of Tests (#TE) - The frequency will be measured by the number of tests created in the course. The tests are considered both a learner-content interaction (because of the automatic feedback) and a learner-instructor interaction (as instructors can add additional feedback and are required to grade short-answer/essay responses). All assignments that have been assigned a grading period by the instructor will be included.

- Frequency of Discussion Boards (#DB) - The frequency will be measured by the number of discussion boards created in the course. Discussion boards represent both a learner-learner interaction event and a learner-instructor interaction when grade feedback is provided. All assignments that have been assigned a grading period by the instructor will be included.

Block 3.

- Curricular Subject Area (CSA) - The curricular subject area will be added to the regression equation for each dependent variable. Previous research predicts that this will not significantly add variance to student learning and achievement. The curricular subject areas will be categorized by the subject areas designated by the organization. The categories will be: career and technical education (CTE), fine arts, health/physical education, English, math, science, social studies, and world languages. There are nine categories for analysis. A dummy variable will be created for each category, resulting in eight dummy variables. In the meta-analysis by Başol and Johanson (2009), the 78 studies were found to differ in their effect sizes according to the subject matter variable that included education, psychology, mathematics, physics, and chemistry. Among the levels of subject matter, the subject level math had the largest mean effect size value (Başol & Johanson, 2009). The curricular subject area of math will be used in this study as the reference category for the creation of dummy variables. The dummy variables are as follows: CTEdummy, FAdummy, PEdummy, LAdummy, SCIdummy, SSdummy, and WLdummy.

The course length variable will be important to the posttest analysis, but will not be added to the regression equation. Semester courses are 18 weeks in length and year-long courses are 36 weeks in length. Final grades are calculated per 18-week semester. There is not a year-long final grade. Posttests are completed after 18 weeks for semester-long courses and after 36 weeks for year-long courses. Since posttests are not completed at the end of each semester in year-long courses, the difference between semester-long and year-long courses will need to be evaluated. Since year-long courses would contain two semesters of LMS tool frequency they should not be combined and compared with semester-long courses. Course length is a dichotomous variable and will code 36 week-long courses as 1 and 18 week-long courses as 0.

Analyses

The models will be developed using hierarchical multiple regressions. Multiple R will be determined for the actual values of the outcome variable and the values predicted by the multiple regression model. The two dependent variables being evaluated will be semester final grades and posttest scores. Pretest scores will be used as a control variable for the dependent variables and entered into Block 1. The independent variables are divided into two blocks. Block 2 will include the frequency of LMS tool use variables. Block 3 will include the curricular subject area variable. The predictive variable for curricular subject area consists of eight “dummy” variables. Each block of independent variables will be added to the hierarchical multiple regression analysis using the simultaneous-enter method.

Highly correlated variables are problematic for regression analysis, and independent variables will be evaluated to determine the level of collinearity. The inter-item covariance matrix and scatter plots will be used to determine if there is a linear relationship. In addition to studying the main effect of each of the independent variables, if variables are highly correlated, a new interaction variable will be created to determine the significance of the interaction. The collinearity will be measured using the variance inflation factor (VIF). The VIF for each independent variable will be evaluated to determine if high collinearity exists between the variables. A VIF of 10 or greater indicates there is a high collinearity between variables and will require a modification before continuing with the study (UCLA Institute for Digital Research and Education, n.d.). If only one independent variable of frequency of LMS tool use is found to have a VIF above 10, it will be dropped from the study.

This study has used expert knowledge of the LMS and pedagogical literature support to determine the LMS tool predictor variables and will use the enter method to enter all independent variables into the equation simultaneously. The simultaneous enter method, which is useful when the number of predictor variables is small, will help determine which independent variables create the best prediction equation. Each predictor will be assessed for what it offers to the predictor model. This study will analyze both the relationship between the variables and the predictive factor of the frequency of updates, assignments, tests, and discussion boards. The goal is to correctly predict the model for student achievement (semester final grades) and the model for student learning (posttest scores) based on the frequency of updates, assignments, tests, and discussion boards. The pretest score will also be used as the prior knowledge control predictor in the regression analysis for student learning and for student achievement. Outlier analyses will be conducted to determine if any factors have high or low influence on the linear regression. The hierarchal multiple regression will determine what each successive model adds to the prediction of the dependent variables using the "R Square Change" value.

Procedure

The proposed procedure will include three main steps: logging the data, data pre-processing, and data mining as identified in the proposed framework for data mining in e-learning (Kazanidis, Valsamidis, Theodosiou, & Kontogiannis, 2009). All pre-existing data will be de-identified by the Research and Evaluation Branch at the organization being studied. The researcher will be provided the data on two flash drives.

Logging the data. Step 1, logging the data, will be initiated by the Research and Evaluation Branch at the organization through a research request for data submitted by the researcher. The request for research data will include the frequency count of the LMS tools by course, SIS data, and pretest/posttest scores. The Research and Evaluation Branch at the organization will de-identify all data before the researcher receives the information. The SIS data contain student demographics and course semester final grades. Pretest and posttest scores are collected by the educational technologists at the VHS. The pretest and posttest data will be sent to the Research and Evaluation Branch to align with the SIS data. The pretest and posttest data must be aligned with the demographics in order to be able to complete exclusions based on ELL and special education status. The demographics, semester course grades, pretest, posttests, and LMS tools will be sent to the researcher in a de-identified format. The data will be imported to a statistical software package. The first dataset will be the student data that includes demographic data, semester final grades, pretest scores, and posttest scores. The second dataset will be the frequency of LMS tools by semester that includes frequency of updates, frequency of assignments, frequency of tests, and frequency of discussion boards. Any courses that do not include data for each field in the datasets will be excluded from the study.

Data pre-processing. Step 2, data pre-processing will clean up the data through statistical methods. The course will be identified by its course code and the course code will be used to add the curricular subject area and course length variables to the frequency data table. The individual student scores for semester final grade, pretest, and posttest will be included in the new frequency data table. The students' ELL designation, special education designation, and mid-semester transfer status will be used for exclusions. The LMS tool dataset will be used to identify each LMS tool used in the course and count the number of instances of each tool for the frequency data table. The researcher will then have a frequency data table for each student record that includes: course ID, curricular subject area, course length, pretest score, semester final grade, posttest score, frequency of updates, frequency of assignments, frequency of tests, and frequency of discussion boards. Any courses that do not contain pretest data will be excluded from the analyses.

Data mining. Step 3, data mining, is the running of the analyses proposed in this study. The dependent variables semester final grades and posttest will be analyzed separately. The pretest control variable will be added before any block of independent variables for the semester final grades and posttest regression to determine R^2. The semester final grade regression equation for student achievement will consist of hierarchical multiple regressions to determine the coefficient of multiple determination (R^2):

1. Model 1 - The control variable pretest score will be entered first and the R^2 will be evaluated for significance.
2. Model 2 - Block 2, consisting of the frequency independent variables will be simultaneously entered into the analysis. R^2 for each independent variable and the overall frequency block will be evaluated for significance.

3. Model 3 - Block 3, consisting of curricular subject area dummy variable, will be simultaneously entered into the analysis. R^2 for curricular subject area will be evaluated for significance.

The posttest score regression equation for student learning will consist of hierarchical multiple regressions to determine the coefficient of multiple determination (R^2):

1. Model 1 - The control variable pretest score will be entered first and the R^2 will be evaluated for significance.
2. Model 2 - Block 2, consisting of the frequency independent variables will be simultaneously entered into the analysis. R^2 for each independent variable and the overall frequency block will be evaluated for significance.
3. Model 3 - Block 3, consisting of curricular subject area, will be entered into the analysis. R^2 for curricular subject area will be evaluated for significance.

The curricular subject area will consist of dummy variables. If the curricular subject area dummy variables are found not to add significant variance to the regression equations, then no further regressions will be run. If the curricular subject area is found to improve significance of the equation, each curricular subject area's dummy variable will be analyzed using the multiple regression Model 2.

Role of the researcher. The researcher will be responsible for completing a research request through the organization's Research and Evaluation Branch. The researcher will be responsible for securing and storing the data once received. The researcher will use the pre-existing data to conduct analyses using statistical software. There will be no direct contact with instructors or students of the courses. The researcher will not modify any course content or implement any changes to courses. The researcher will only be in contact with the organization's

Research and Evaluation Branch. The researcher will not affect the teaching and learning of instructors and students at the school being studied.

CHAPTER IV

Results

Descriptive Statistics

The initial data received for the analysis contained 7,117 student records. Each record could contain two semester final grades if the record was for a year-long course or one semester final grade for a semester-long course. Student records that did not contain a pretest score were excluded from the analysis. This resulted in the removal of 4,700 records because of missing student scores or because the course did not include a pretest. The number of records that did not contain pretest scores was surprising as pretest and posttest assessments are recommended by the organization. But including a pretest and posttest was a teacher decision and a student did not receive a negative mark on their final grade if they did not complete the assessment. For the remaining student records with pretest scores, each contained a corresponding posttest score. For semester final grades there were 704 incomplete records that had a pretest score but did not contain a semester final grade and were thus also excluded from analysis. The remaining student data for analysis contained 2,188 posttest scores and 3,043 semester final grades. The reduced sample for gender of the students was 41% male and 59% female. The grade level of the students was ninth (1.2%), tenth (7.0%), eleventh (12.3%), twelfth (79.4%), and thirteenth (0.1%). The thirteenth grade was due to the semester final grade being entered after the graduation of students who had completed the course while enrolled in twelfth grade. Gender and grade level were identified for demographic purposes and were not used in the regression analysis.

Course length and curricular subject area were identified as required variables for the regression analyses. There were 1,187 semester-long courses and 1,001 year-long courses. The eight curricular subject areas were career and technical education, English, fine arts, health and physical education, math, science, social studies, and world languages. The curricular subject area of English accounted for the lowest frequency of posttest scores and semester final grades. The curricular subject area of social studies accounted for the highest frequency of courses for posttest scores and semester final grades.

Score frequencies. The scale for pretest scores, posttest scores, and semester final grades was 0 to 100. As shown in Table 1, pretest scores had the highest standard deviation and only slight positive skewness and kurtosis. The posttest scores had positive skewness and were leptokurtic. The semester final grades also had positive skewness and were leptokurtic. Posttest scores and semester grades were expected to have positive skewness, as learning had occurred over the length of the course. The size of the sample allowed for absolute skewness value of < 2 or an absolute kurtosis < 4 to be considered normal (West, Finch, & Curran, 1995).

Table 1
Descriptive Statistics for Semester Final Grade, Pretest, and Posttest

	Semester Final Grade	Pretest	Posttest
N Valid	3043	2188	2188
Missing	0	0	0
Std. Deviation	9.905	20.852	16.752
Variance	98.106	434.803	280.614
Skewness	-1.167	-0.079	-1.135
Std. Error of Skewness	0.044	0.052	0.052
Kurtosis	2.644	-0.601	1.140
Std. Error of Kurtosis	0.089	0.105	0.105
Range	90	99	100

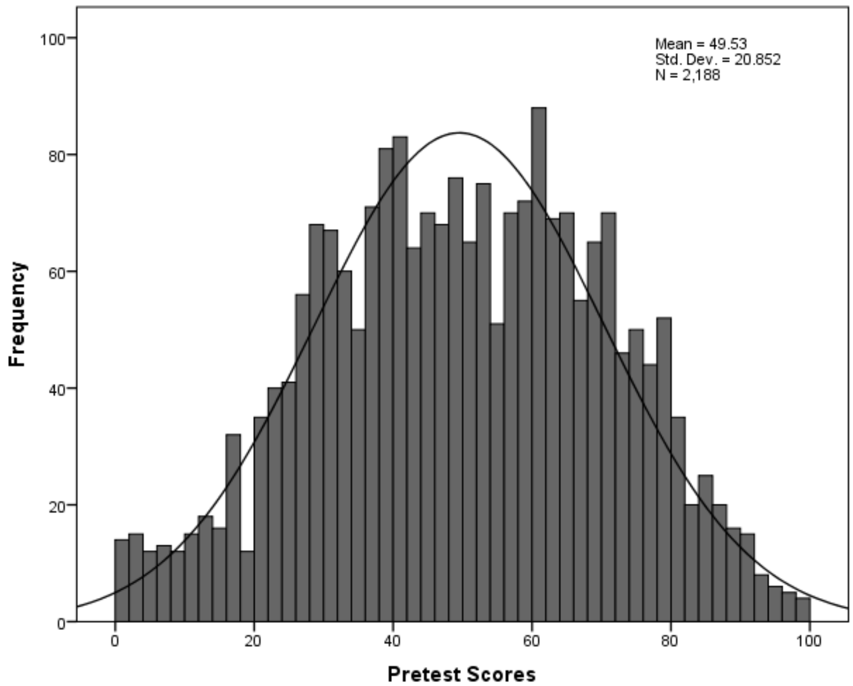

Figure 1. Pretest score frequency and value on a scale of 0 to 100.

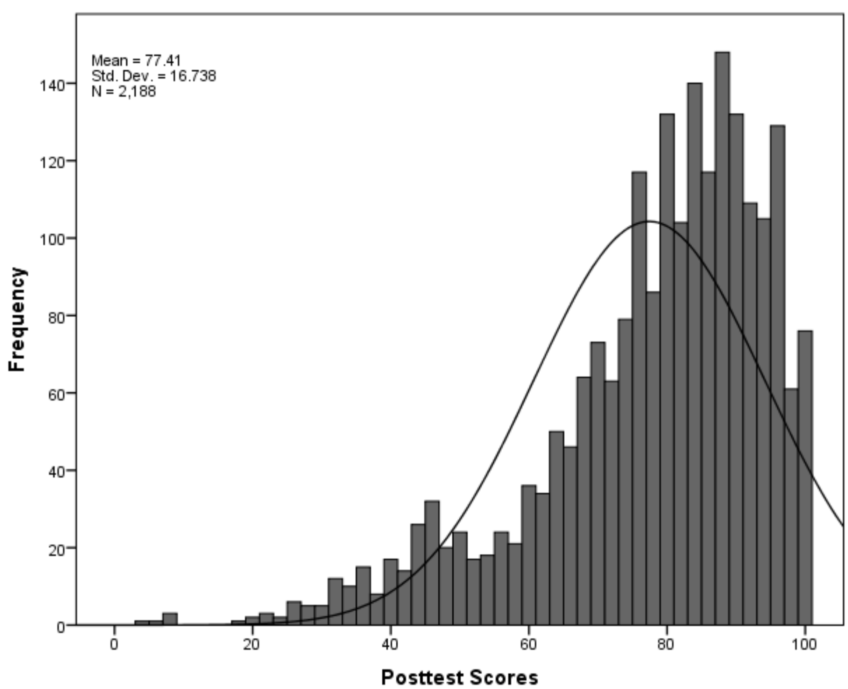

Figure 2. Posttest score frequency and value on a scale of 0 to 100.

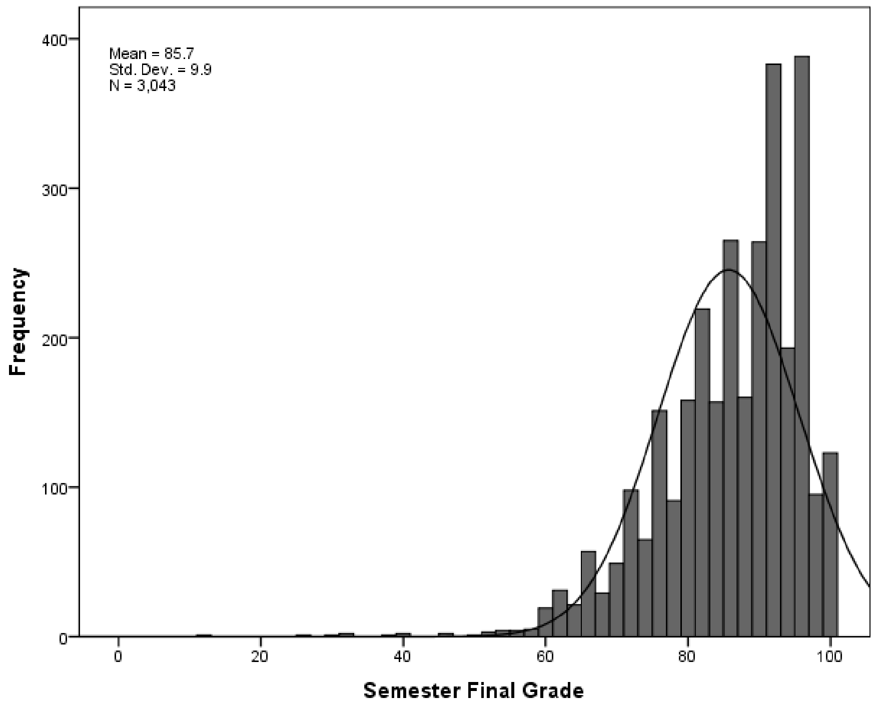

Figure 3. Semester final grade frequency and value on a scale of 0 to 100.

LMS Tool Frequencies. The mean values for each LMS tool, by curricular subject area, is displayed in Figure 4. The LMS assignment tool was the most used tool in career and technical education, health and physical education, science, social studies, and world languages. The LMS update tool was most used in English and fine arts. The LMS test tool was most frequently used in math. The LMS discussion board tool was the least used tool in all curricular subject areas. The mean score across all curricular subject areas for the LMS tools was updates (26.3), assignments (32.6), tests (27.4), and discussion boards (5.6).

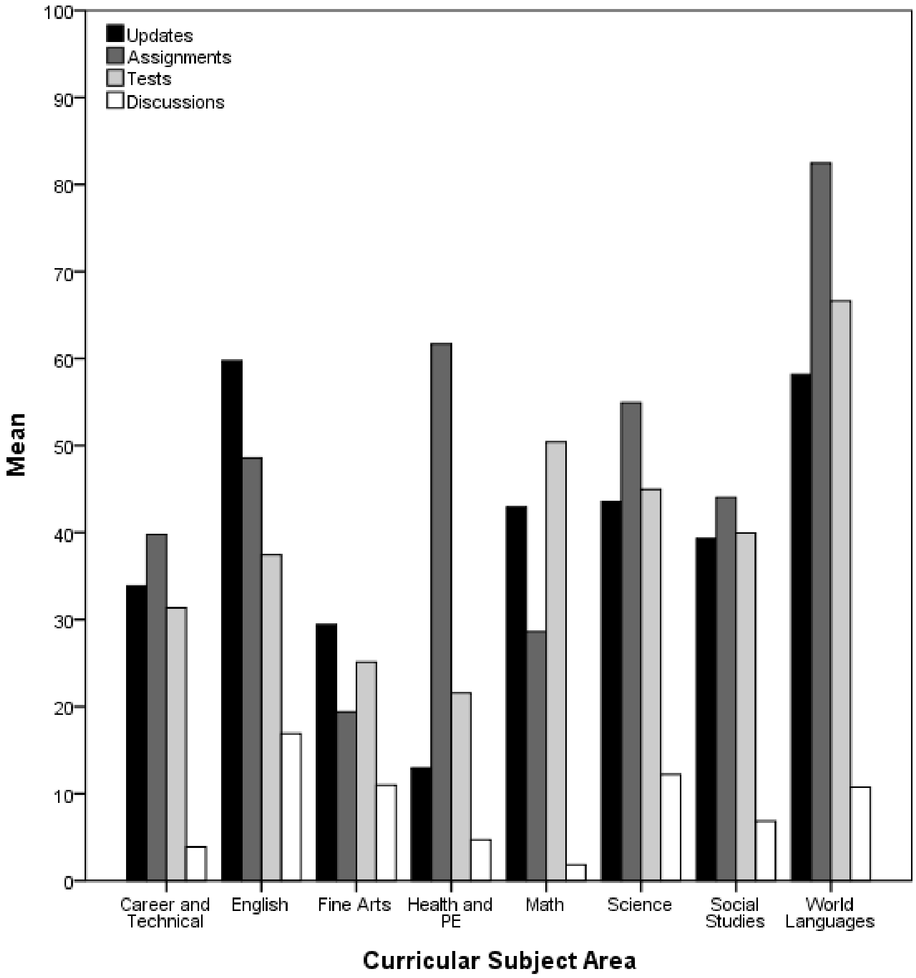

Figure 4. The mean frequency of LMS updates, assignments, tests, and discussion boards tools by curricular subject area

Sample Size and Power

There were 233 courses in the data used for the analyses. Year-long courses were split by semester, which created 324 unique courses for semester final grade analysis. The analyses contained 2,188 posttest scores and 3,043 semester final grades for students. The data were analyzed using G*Power (v3.1.9.2) post hoc power analysis to compute achieved power. The test family selected was F tests and the statistical test selected was linear multiple regression: fixed model, R^2 deviation from zero. The effect size (f^2) was set to .02 for the smallest effect size that would be significant. To account for inflated alphas due to conducting multiple regression equations, a more conservative significance criterion value of .001 for the alpha(α) error probability was chosen. The significance value of .001 was chosen to decrease the risk of a Type I error, or more simply stated, of falsely detecting an effect that was not present. For semester final grades, the sample size was 3,043 and contained 12 predictors. For posttest scores the sample size was 2,188 and contained 12 predictors. The statistical power for semester final grades was .998 and for posttest scores was .95. The sample size and power values allowed for the detection of small effects, with a high degree of probability that the test correctly rejected the null hypothesis.

With high statistical power to reject the null hypothesis, effect sizes were calculated to determine if the models and coefficients were practically significant as well as statistically significant. To determine effect size, Cohen's f^2 is appropriate for hierarchical multiple regression (Selya, Rose, Dierker, Hedeker, & Mermelstein, 2012). Using the formula $f^2 = R^2 / (1-R^2)$, effect sizes were calculated for each model and significant coefficients. According to Cohen (1992), effect sizes for f^2 are small (.02), medium (.15), and large (.35). The labels of small, medium and large were used to describe values for f^2 that fell within the range identified by Cohen (1992). For the purpose of this study, effects below .02 were considered to have no effect.

Research Question 1

RQ1: To what extent does the frequency of LMS update, assignment, test, and discussion board tools used by instructors predict semester final grade achievement by students in online secondary courses after controlling for prior learning?

To test first the research question, a hierarchical multiple regression was conducted to determine the predictive effect of the LMS tools on semester final grade achievement. The dependent variable was student semester final grades. The control variable (pretest) was entered into Block 1. The LMS tools of updates, assignments, tests, and discussion boards were entered into Block 2. The dummy variables for curricular subject area were entered into Block 3, using math courses (MAT) as the comparison group. The courses offered each year were selected by the virtual school principal and support staff and the data provided for this study were organized by school year. The dataset was split by the two school years provided by using the SPSS split command for the school year variable. The school years were labeled SY1415 for school year 2014 to 2015 and SY1516 for school year 2015 to 2016. The entire SPSS output is available upon request, reference Appendix A.

Regression Assumption Analysis. The following assumptions for a regression equation were analyzed: linearity, normality, homoscedasticity, multicollinearity, independent of errors/autocorrelation, and outliers/influential cases. An analysis of the standard residuals was conducted to identify any outliers, resulting in identification of fifteen cases that could be considered outliers. The fifteen cases did not have critical values for Mahalanobis distance. To assess if these cases had influence, the DFBETAs and Cook's distance values were analyzed. Cook's distance values were $< .01$ and did not indicate high influence. The standardized DFBETAs for pretest, updates, assignments, tests, and discussion boards were assessed. The range was minimum (-0.24) and maximum (0.18), which are both less than the accepted maximum > 2 and minimum < -2. It can be concluded that the outliers were not influential cases within the 3,043 analyzed cases.

To assess whether multicollinearity was present, the collinearity statistics of tolerance and variance inflation factor (VIF) were used. A tolerance value of $< .10$ and a VIF of > 5 may indicate high multicollinearity (Mertler & Vannatta, 2005). The lowest tolerance value in Model

3 for SY1415 and SY1516 was social studies at .38. The highest VIF in Model 3 for SY1415 and SY1516 was social studies at 2.64. Based on the tolerance and VIF values, multicollinearity was not a concern. To verify that the residual terms were uncorrelated, a Durbin-Watson test was conducted. Durbin-Watson values of 2 or greater indicate no autocorrelation and values less than 1 indicate strong positive autocorrelation. A Durbin-Watson value of 1.82 (SY1415) and 1.91 (SY1516) were calculated. The values were closer to 2 than to 1 and indicate a slight positive autocorrelation. The data met the assumption of independent errors and did not have autocorrelation.

The assumptions of normality, homoscedasticity, and linearity were evaluated by graph interpretation. The distribution of residuals in Figure 5 was very close to the normal fit line. The normal P-P plot shown in Figure 6 had points that were very close to the goodness of fit line. The data were concluded to be normally distributed and the assumption of normality was met.

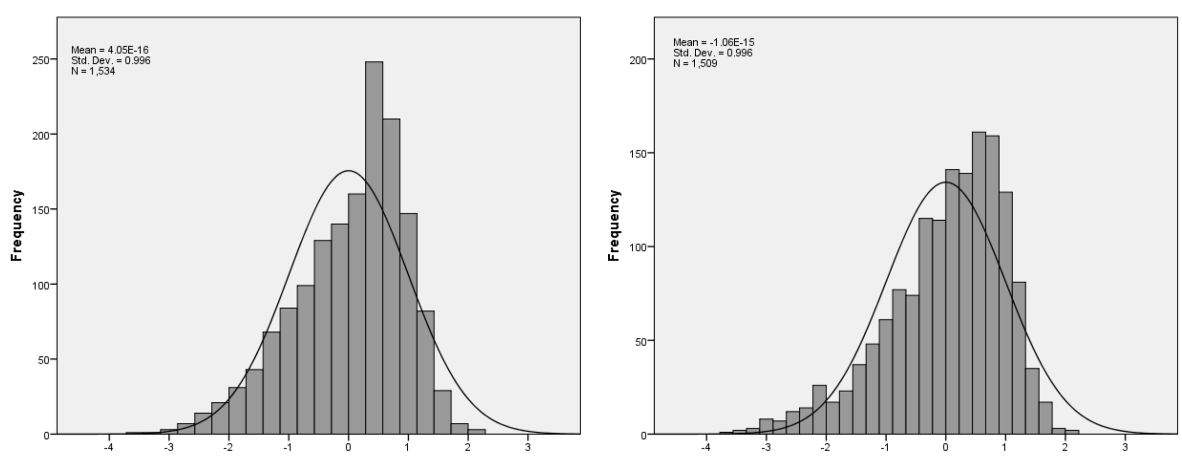

Figure 5. The dependent variable semester final grade and the regression standardized residual with normal curve fit line for SY1415 and SY1516.

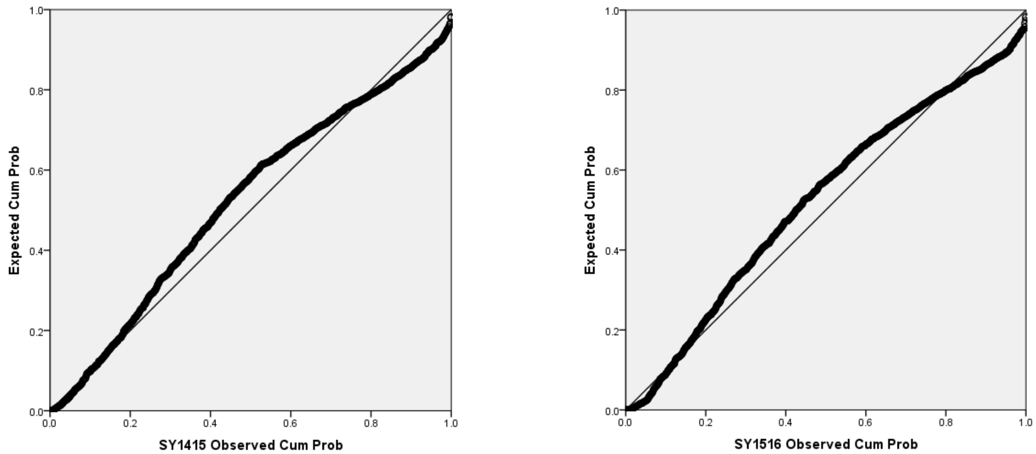

Figure 6. Normal P-P plot of the standardized residual for the dependent variable semester final grade for SY1415 and SY1516.

A scatterplot was evaluated to test the assumption of homoscedasticity and linearity. The scatterplot of standardized residuals and standardized predicted values displayed in Figure 7 indicated that there was no pattern to the residuals plotted against the fitted values. Heteroscedasticity was not present, as there was not a noticeable cone-shape pattern; therefore homoscedasticity could be assumed. Linearity was also confirmed, as the plot was roughly rectangular within +3 and -3 standard deviations.

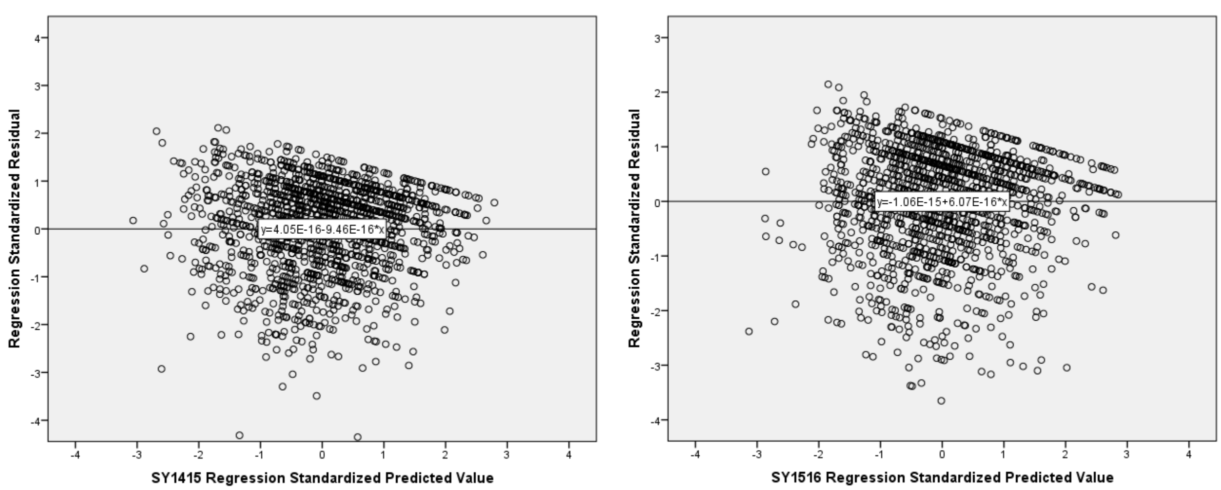

Figure 7. Scatterplot of standardized residual values and standardized predicted values with a linear fit line at total for SY1415 and SY1516.

Research Question 1 Summary

A hierarchical multiple regression was conducted to determine the accuracy of the independent variables in predicting semester final grades. The control variable of pretest scores [Pretest] was entered into Block 1. The independent variables of frequency of updates [Updates], frequency of assignments [Assignments], frequency of tests [Tests], and frequency of discussion boards [Discussions] were entered into Block 2. The independent dummy variables for curricular subject areas of career and technical education, English, fine arts, health and PE, science, social studies, and world languages were entered into Block 3. The curricular subject area of math was used as the comparison group in Block 3. The data were split by school year and labeled by SY1415 and SY1516.

The regression results in Table 2 and Table 3 indicated that the overall model significantly predicted semester final grades for SY1415, $R^2 = .11$, $R^2_{adj} = .10$, $F(12, 1521) = 15.59$, $p < .001$, and for SY1516, $R^2 = .10$, $R^2_{adj} = .10$, $F(12, 1496) = 14.38$, $p < .001$. The adjusted overall model accounted for 10% of the variance in semester final grades. The control variable Pretest in Model 1 significantly predicted semester final grades for SY1415, $R^2 = .09$, $R^2_{adj} = .08$, $F(1, 1532) = 141.62$, $p < .001$, and for SY1516, $R^2 = .03$, $R^2_{adj} = .03$, $F(1, 1507) = 50.89$, $p < .001$. The pretest scores accounted for 9% of the overall variance in SY1415 and 3% of the overall variance in SY1516. The addition of the LMS tools of updates, assignments, tests, and discussions in Model 2 significantly added predictive power for SY1415, $\Delta R^2 = .01$, $\Delta F(4, 1528) = 4.88$, $p = .001$, and for SY1516, $\Delta R^2 = .02$, $\Delta F(4, 1503) = 6.46$, $p < .001$. The addition of the LMS tools to the model contributed 1% for SY1415 and 2% for SY1516 prediction of variance to the overall model. The addition of the dummy curricular subject area (career and technical education, English, fine arts, health and PE, science, social studies, and world languages) in Model 3 added predictive power for SY1516, $\Delta R^2 = .05$, $\Delta F(7, 1496) = 12.97$, $p < .001$. The significance value for SY1415 was above $p < .001$ and therefore considered not significant.

Table 2
Model Summary for Semester Final Grade by School Year

School Year	Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics: R Square Change	F Change	df1	df2	Sig. F Change
SY1415	1	.291[a]	.085	.084	9.609	.085	141.616	1	1532	.000
	2	.310[b]	.096	.093	9.560	.012	4.878	4	1528	.001
	3	.331[c]	.110	.102	9.511	.013	3.256	7	1521	.002
SY1516	1	.181[a]	.033	.032	9.597	.033	50.889	1	1507	.000
	2	.221[b]	.049	.046	9.529	.016	6.456	4	1503	.000
	3	.322[c]	.103	.096	9.274	.054	12.965	7	1496	.000

a. Predictors: (Constant), Pretest
b. Predictors: (Constant), Pretest, Updates, Assignments, Discussions, Tests
c. Predictors: (Constant), Pretest, Updates, Assignments, Discussions, Tests, Career and Technical Education, Science, English, Fine Arts, World Languages, Health and PE, Social Studies

Table 3
ANOVA for Semester Final Grades by School Year

School Year	Model		Sum of Squares	df	Mean Square	F	Sig.
SY1415	1	Regression	13074.806	1	13074.806	141.616	.000[b]
		Residual	141442.693	1532	92.326		
		Total	154517.499	1533			
	2	Regression	14858.179	5	2971.636	32.512	.000[c]
		Residual	139659.320	1528	91.400		
		Total	154517.499	1533			
	3	Regression	16920.077	12	1410.006	15.586	.000[d]
		Residual	137597.422	1521	90.465		
		Total	154517.499	1533			
SY1516	1	Regression	4687.301	1	4687.301	50.889	.000[b]
		Residual	138806.896	1507	92.108		
		Total	143494.196	1508			
	2	Regression	7031.890	5	1406.378	15.490	.000[c]
		Residual	136462.306	1503	90.793		
		Total	143494.196	1508			
	3	Regression	14836.936	12	1236.411	14.377	.000[e]
		Residual	128657.261	1496	86.001		
		Total	143494.196	1508			

a. Dependent Variable: Semester Final Grade
b. Predictors: (Constant), Pretest
c. Predictors: (Constant), Pretest, Updates, Assignments, Discussions, Tests
d. Predictors: (Constant), Pretest, Updates, Assignments, Discussions, Tests, Career and Technical Education, Science, English, Fine Arts, World Languages, Health and PE, Social Studies
e. Predictors: (Constant), Pretest, Updates, Discussions, Tests, Assignments, Social Studies, Science, World Languages, Fine Arts, English, Career and Technical Education, Health and PE

To determine if the overall model was practically significant as well as statistically significant, effect sizes were calculated for each model to assess the magnitude of an observed effect. Using the formula, $f^2 = R^2 / (1-R^2)$, the overall effect size was $f^2 = .12$ for SY1415 and $f^2 = .11$ for SY1516. Based on the effect size calculations it can be inferred that the overall model had a small effect. However, a review of Table 4 shows the beta weights for LMS Tools entered into Model 2 had different coefficients that were significant for SY1415 and SY1516. For SY1415, updates, assignments and discussions were significant at $p < .05$, but were above the $p < .001$ threshold set for this study and are therefore considered non-significant along with the LMS test tool. For SY1516, Assignments $\beta = -.132$, $t(1503) = -5.05$, $p < .001$, 95% CI [-0.062, -0.027], $f^2 = .017$, significantly contributed to the model. The LMS assignment tool was also a negative beta, and therefore an inverse relationship to the semester final grades. The LMS update, test, and discussion board tools were not significant for SY1516.

Table 4
Model 2 Coefficients for Semester Final Grades for SY1415 and SY1516

School Year	Model		Standardized Coefficients Beta	t	Sig.	95.0% Confidence Interval for B Lower Bound	95.0% Confidence Interval for B Upper Bound	Correlations Partial
SY1415	2	(Constant)		86.299	.000	75.421	78.930	
		Pretest	.299	12.228	.000	0.126	0.174	.299
		Updates	.053	2.142	.032	0.002	0.056	.055
		Assignments	-.064	-2.554	.011	-0.047	-0.006	-.065
		Tests	.044	1.720	.086	-0.003	0.044	.044
		Discussions	.055	2.221	.027	0.009	0.140	.057
SY1516	2	(Constant)		86.183	.000	80.871	84.638	
		Pretest	.190	7.392	.000	0.063	0.108	.187
		Updates	.043	1.652	.099	-0.006	0.075	.043
		Assignments	-.132	-5.046	.000	-0.062	-0.027	-.129
		Tests	-.010	-0.406	.685	-0.032	0.021	-.010
		Discussions	-.007	-0.272	.786	-0.085	0.064	-.007

Additionally, a review of the beta weights in Table 5 when curricular subject area dummy predictors were added into Model 3 confirmed that the LMS assignment tool maintained its significance and negative relationship to semester final grades. The curricular subject area dummy variables in Model 3 significantly differed from the compared variable math in predicting semester final grades. For SY1415, Social Studies $\beta = .12$, $t(1521) = 3.32$, $p = .001$, 95% CI [1.236, 4.426], $f^2 = .007$, was a significant predictor of semester final grades. For SY1516, Career and Technical Education $\beta = .13$, $t(1496) = 3.50$, $p < .001$, 95% CI [1.494, 5.318], $f^2 = .008$; English $\beta = .13$, $t(1496) = 4.11$, $p < .001$, 95% CI [3.150, 8.904], $f^2 = .011$; Fine Arts $\beta = .12$, $t(1496) = 3.63$, $p < .001$, 95% CI [2.144, 7.181], $f^2 = .009$; Health and PE $\beta = -.13$, $t(1496) = -3.56$, $p < .001$, 95% CI [-6.7753, -1.965], $f^2 = .009$, were significant predictors of semester final grades. The effect sizes for the statistically significant curricular subject area variables were below .02 and therefore were found to have no effect.

Table 5
Model 3 Coefficients for Semester Final Grades for SY1415 and SY1516

School Year	Model		Standardized Coefficients Beta	t	Sig.	95.0% Confidence Interval for B Lower Bound	95.0% Confidence Interval for B Upper Bound	Correlations Partial
SY1415	3	(Constant)		73.656	.000	73.291	77.302	
		Pretest	.312	12.086	.000	0.131	0.182	.296
		Updates	.056	2.151	.032	0.003	0.059	.055
		Assignments	-.066	-2.290	.022	-0.051	-0.004	-.059
		Tests	.050	1.946	.052	0.000	0.047	.050
		Discussions	.032	1.215	.224	-0.026	0.113	.031
		CTE	.069	2.199	.028	0.229	4.007	.056
		English	.003	0.114	.909	-2.265	2.544	.003
		Fine Arts	.069	2.236	.025	0.311	4.749	.057
		Health/PE	.036	1.088	.277	-1.205	4.204	.028
		Science	.083	2.652	.008	0.719	4.807	.068
		Social Studies	.123	3.316	.001	1.136	4.426	.085
		World Languages	.008	0.214	.831	-1.672	2.082	.005
SY1516	3	(Constant)		74.522	.000	80.483	84.834	
		Pretest	.214	8.033	.000	0.073	0.120	.203
		Updates	-.062	-2.130	.033	-0.094	-0.004	-.055
		Assignments	-.062	-2.112	.035	-0.041	-0.001	-.055
		Tests	-.024	-0.926	.355	-0.039	0.014	-.024
		Discussions	-.057	-2.074	.038	-0.166	-0.005	-.054
		CTE	.125	3.495	.000	1.494	5.318	.090
		English	.132	4.109	.000	3.150	8.904	.106
		Fine Arts	.118	3.632	.000	2.144	7.181	.093
		Health/PE	-.133	-3.564	.000	-6.775	-1.965	-.092
		Science	.002	0.058	.954	-2.015	2.138	.001
		Social Studies	.109	2.745	.006	0.715	4.292	.071
		World Languages	.003	0.074	.941	-1.836	1.980	.002

To summarize the results for research question 1, the overall model significantly predicted semester final grades for SY1415, $R^2 = .11$, $R^2_{adj} = .10$, $F(12, 1521) = 15.59$, $p < .001$, and for SY1516, $R^2 = .10$, $R^2_{adj} = .10$, $F(12, 1496) = 14.38$, $p < .001$. The control variable Pretest was 8.5% of the total 11% variance explained for SY1415 and 3.3% of the total 10.3% of the variance explained for SY1516. The inclusion of the LMS tools of updates, assignments, tests, and discussion boards added 1.2% variance explained for SY1415 and 1.6% variance explained for SY1516. The inclusion of the curricular subject area variables added 1.3% variance explained for SY1415 and 5.4% variance explained for SY1516. The effect size (f^2) for the R Square Change (ΔR^2) in models for SY1415 was small (Model 1 = .09) and no effect (Model 2 = .01, Model 3 = .01). The effect size (f^2) for the R square change (ΔR^2) in models for SY1516 was small (Model 1 = .03, Model 2 = .02, and Model 3 = .06). The independent variable assignments was the only LMS tool that was a significant predictor in the full model, but had no effect size. The curricular subject areas had significant differences from the math comparison group, but effect size was not significant. The significant differences in the predictive power of curricular subject areas will be further analyzed in Research Question 3.

Research Question 2

RQ2: To what extent does the frequency of LMS update, assignment, test, and discussion board tools used by instructors predict posttest learning by students in online secondary courses after controlling for prior learning and does the effect vary by course length?

To test the research question, a hierarchical multiple regression was conducted to determine the predictive effect of the LMS tools on posttest scores. The dependent variable was student semester final grades. The control variable (pretest) was entered into Block 1. The LMS tools of updates, assignments, tests, and discussion boards were entered into Block 2. The dummy variables for curricular subject area were entered into Block 3, using math courses (MAT) as the comparison group. The courses offered each year were selected by the virtual school principal and support staff. The student data provided for courses were organized by school year. The dataset was split by the two school years provided using the SPSS split command for the school year variable. The school years were labeled SY1415 for the school year 2014 to 2015 and SY1516 for the school year 2015 to 2016. To answer if the predictive power varied by course length, the school years were further split by the course length variable. The course length variables were labeled Semester-Long (SL) and Year-Long (YL). The entire SPSS output is available upon request, reference Appendix B.

Regression Assumption Analysis. The following assumptions for a regression equation were analyzed: linearity, normality, homoscedasticity, multicollinearity, independent of errors/autocorrelation, and outliers/influential cases. An analysis of the standard residuals, used to identify any outliers, indicated fifteen cases that might be outliers. The fifteen cases did not have critical values for Mahalanobis distance. To assess if these cases had influence, the DFBETAs and Cook's distance values were analyzed. Cook's distance values were $< .01$ and did not indicate high influence. The standardized DFBETAs for pretest, updates, assignments, tests, and discussion boards were assessed. The range was minimum (-0.24) and maximum (0.18), which are both less than the accepted maximum > 2 and minimum < -2. It can be concluded that the outliers were not influential cases within the 2,188 analyzed cases.

To assess whether multicollinearity was present, the collinearity statistics of tolerance and variance inflation factor (VIF) were used. A tolerance value of $< .10$ and a VIF of > 5 may indicate high multicollinearity (Mertler & Vannatta, 2005). The lowest tolerance value in Model 3 for SY1415 was .20 (Health and PE) and for SY1516 was .19 (Career and Technical

Education). The highest VIF in Model 3 for SY1415 was 5.10 (Health and PE) and for SY1516 was 5.25 (Career and Technical Education). Based on the tolerance and VIF values, multicollinearity was not a concern, as the VIF was close to 5, but tolerance was above the .10 value to indicate concern. To verify that the residual terms were uncorrelated, a Durbin-Watson test was conducted. The data were sorted by course section code, which had semester final grades from a similar course adjacent to one another. Durbin-Watson values of 2 or greater indicate no autocorrelation and values less than 1 indicate a strong positive autocorrelation. The Durbin-Watson values for SY1415 were 1.12 (SL) and 1.75 (YL). The Durbin-Watson values for SY1516 were 1.86 (SL) and 1.36 (YL). There was a slight positive autocorrelation, but the Durbin-Watson values were above 1. The data met the assumption of independent errors and were found not to have autocorrelation.

The assumptions of normality, homoscedasticity, and linearity were evaluated by graph interpretation. Figure 8 shows that the distribution of all four sets of data was very close to the normal fit line. The normal P-P plot shown in Figure 9 had points that were very close to the goodness of fit line. The data were concluded to be normally distributed and the assumption of normality was met.

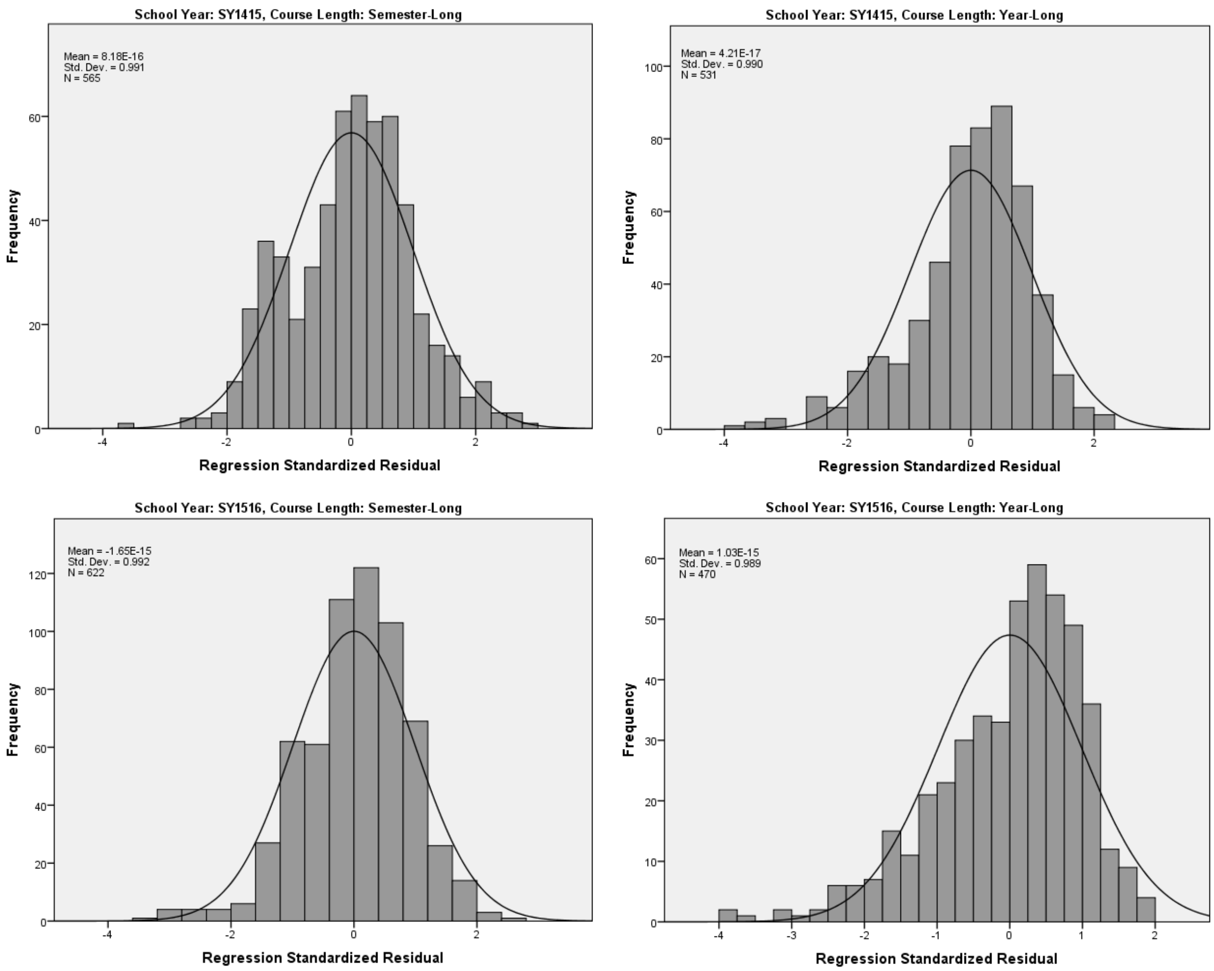

Figure 8. The dependent variable posttest scores and the regression standardized residual with normal curve fit line for SY1415 and SY1516 by Semester-Long and Year-Long course length.

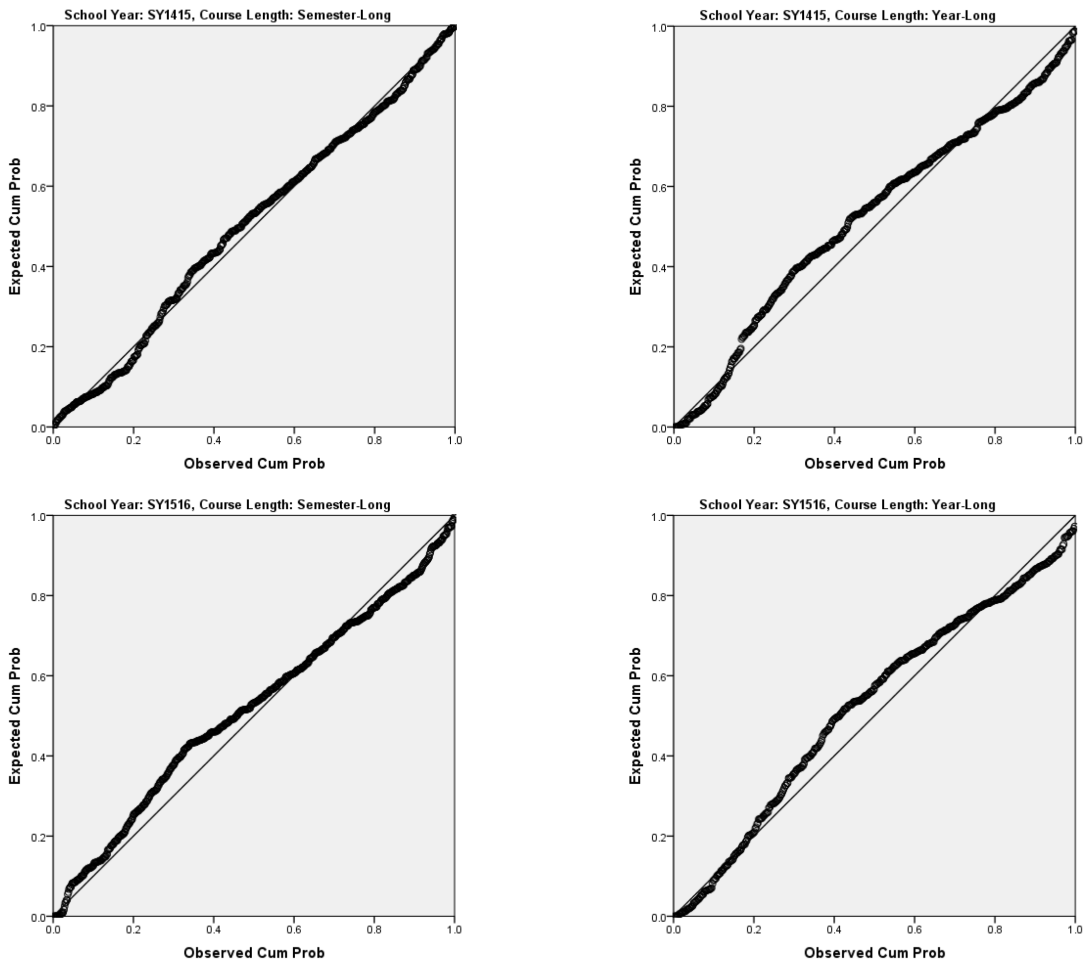

Figure 9. Normal P-P plot of the standardized residual for the dependent variable posttest scores for SY1415 and SY1516 by Semester-Long and Year-Long course length.

A scatterplot was created to test the assumption of homoscedasticity and linearity of the standardized residuals by predicted values. The scatterplot of standardized residuals and standardized predicted values in Figure 10 showed that there was no pattern to the residuals plotted against the fitted values. A slight tapering of the positive values was visible, which would indicate some heteroscedasticity. Linearity was also confirmed, as the plot was roughly rectangular within +3 and -3 standard deviations.

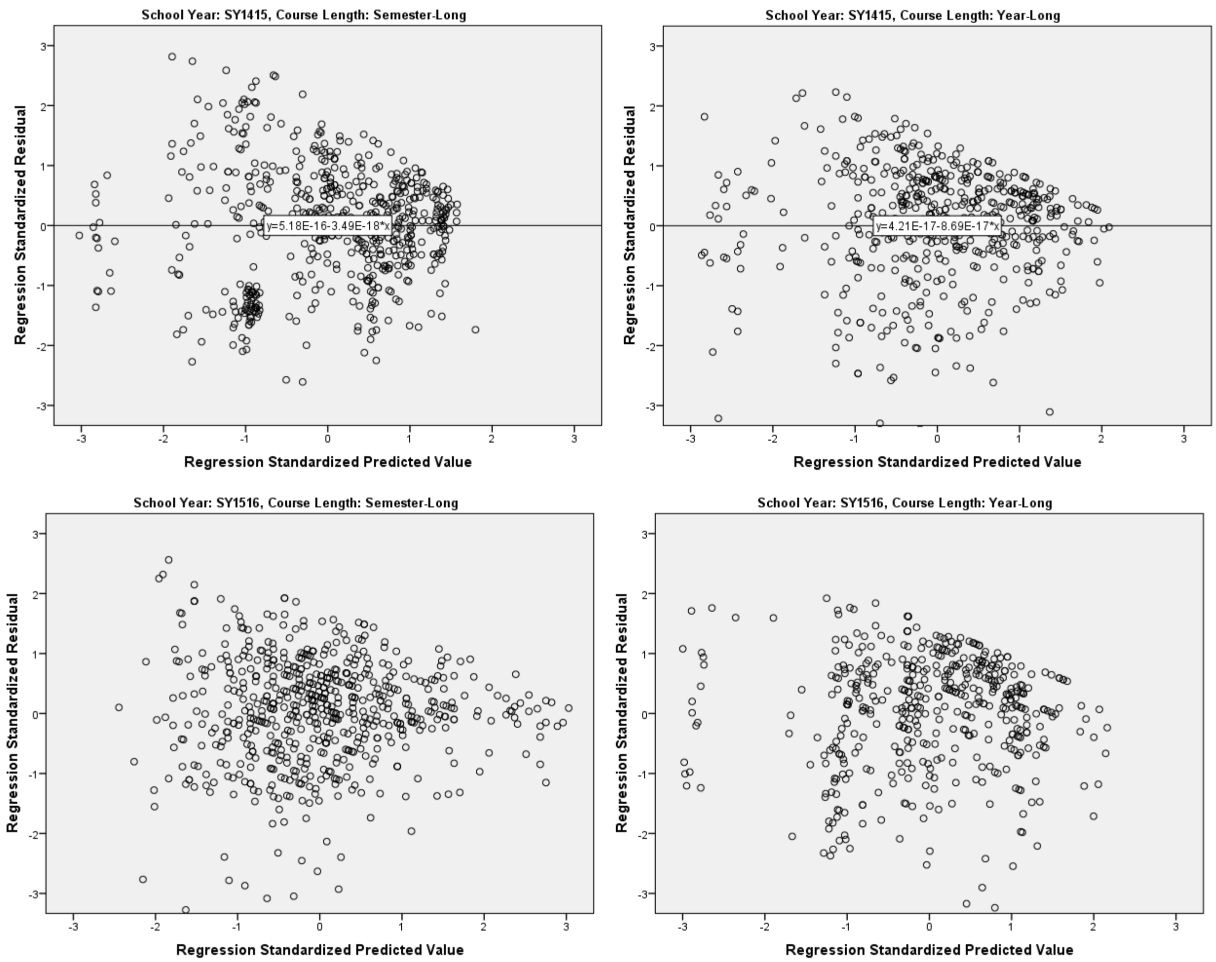

Figure 10. Scatterplot of standardized residual values and standardized predicted values with a linear fit line at total for SY1415 and SY1516 by Semester-Long and Year-Long course length.

Research Question 2 Summary

A hierarchical multiple regression was conducted to determine the accuracy of the independent variables in predicting posttest scores. The control variable of pretest scores [Pretest] was entered into Block 1. The independent variables of frequency of updates [Updates], frequency of assignments [Assignments], frequency of tests [Tests], and frequency of discussion boards [Discussions] were entered into Block 2. The independent dummy variables for curricular subject area (Career and Technical Education, English, Fine Arts, Health and PE, Science, Social Studies, World Languages) were entered into Block 3. The curricular subject area for math was used as the comparison group in Block 3.

The data were split by school year and labeled SY1415 and SY1516. The data were then further split by the course length variable. Year-long courses had a posttest score that spanned two semesters of content and could not be directly compared to semester-long posttest scores, as the frequency of LMS tools for year-long courses also contained two semesters. As shown in Figure 11, the year-long data did not contain health and PE courses and the semester-long data did not contain science and world languages courses. The only curricular subject area that had data for one school year but not the other was fine arts YL. Fine arts YL contained data for SY1415 but not for SY1516.

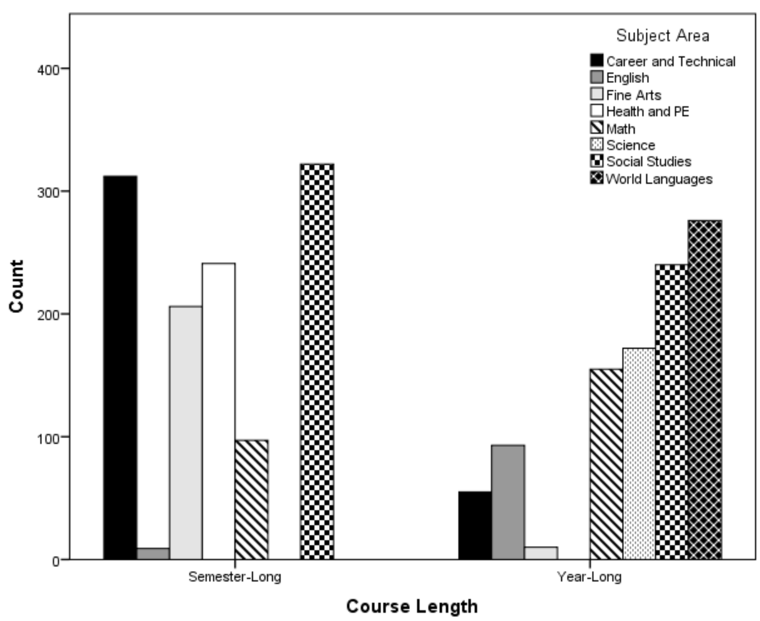

Figure 11. Count of Semester-Long and Year-Long course lengths by curricular subject area.

The regression results in Table 6 and Table 7 indicated that the overall model significantly predicted posttest scores for SY1415 SL, $R^2 = .45$, $R^2_{adj} = .44$, $F(10, 554) = 45.53$, $p < .001$; SY1415 YL, $R^2 = .28$, $R^2_{adj} = .27$, $F(11, 519) = 18.41$, $p < .001$; SY1516 SL, $R^2 = .17$, $R^2_{adj} = .16$, $F(10, 611) = 12.65$, $p < .001$; SY1516 YL, $R^2 = .24$, $R^2_{adj} = .23$, $F(10, 459) = 14.65$, p

$< .001$. The lowest variance accounted for was 17% for SY1516 SL and the highest variance was 45% for SY1415 SL. The control variable for pretest scores (Pretest) in Model 1 significantly predicted posttest scores for SY1415 SL, $R^2 = .06$, $R^2_{adj} = .06$, $F(1, 563) = 36.31$, $p < .001$; SY1415 YL, $R^2 = .12$, $R^2_{adj} = .12$, $F(1, 563) = 69.72$, $p < .001$; SY1516 SL, $R^2 = .09$, $R^2_{adj} = .09$, $F(1, 620) = 62.58$, $p < .001$. SY1516 YL was significant at $p < .05$, but for the purpose of this study SY1516 YL would not be considered significant, as it was greater than $p < .001$. The pretest scores accounted for the highest percentage of variance in SY1415 YL (12%) and the lowest percentage of variance in SY1415 SL (6%). The addition of the LMS update, assignment, test, and discussion board tools in Model 2 significantly added predictive power for SY1415 SL, $\Delta R^2 = .04$, $\Delta F(4, 559) = 6.56$, $p < .001$; SY1415 YL, $\Delta R^2 = .14$, $\Delta F(4, 525) = 24.50$, $p < .001$; SY1516 SL, $\Delta R^2 = .03$, $\Delta F(4, 616) = 4.50$, $p < .001$; SY1516 YL, $\Delta R^2 = .082$, $\Delta F(4, 464) = 10.49$, $p < .001$. The LMS tools contributed an additional 3% (SY1516 SL) to 14% (SY1415 YL) prediction of the variance in the overall model. The addition of the dummy curricular subject area variables (Career and Technical Education, English, Fine Arts, Health and PE, Science, Social Studies, World Languages) in Model 3 significantly added predictive power for SY1516 SL, $\Delta R^2 = .05$, $\Delta F(5, 611) = 7.97$, $p < .001$ and SY1516 YL, $\Delta R^2 = .15$, $\Delta F(5, 459) = 18.25$, $p < .001$. SY1415 was significant at $p < .01$, but for the purpose of this study SY1415 would not be considered significant, as it was greater than $p < .001$. The curricular subject area dummy variables contributed an additional 5% to 15% prediction of the variance in the overall model.

Table 6

Model Summary for Posttest Scores by School Year and Course Length

School Year	Course Length	Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics: R Square Change	F Change	df1	df2	Sig. F Change
SY1415	Semester-Long	1	.246[a]	.061	.059	17.861	.061	36.313	1	563	.000
		2	.320[b]	.103	.095	17.518	.042	6.560	4	559	.000
		3	.672[c]	.451	.441	13.763	.348	70.329	5	554	.000
	Year-Long	1	.341[a]	.116	.115	16.478	.116	69.714	1	529	.000
		2	.505[b]	.255	.248	15.184	.139	24.502	4	525	.000
		3	.530[d]	.281	.265	15.011	.025	3.029	6	519	.006
SY1516	Semester-Long	1	.303[a]	.092	.090	11.406	.092	62.583	1	620	.000
		2	.343[b]	.117	.110	11.280	.026	4.501	4	616	.001
		3	.414[e]	.172	.158	10.973	.054	7.973	5	611	.000
	Year-Long	1	.095[a]	.009	.007	18.040	.009	4.286	1	468	.039
		2	.302[b]	.091	.081	17.351	.082	10.485	4	464	.000
		3	.492[f]	.242	.225	15.933	.151	18.254	5	459	.000

a. Predictors: (Constant), Pretest

b. Predictors: (Constant), Pretest, Updates, Assignments, Discussions, Tests

c. Predictors: (Constant), Pretest, Updates, Assignments, Discussions, Tests, Career and Technical Education, English, Fine Arts, Health and PE, Social Studies

d. Predictors: (Constant), Pretest, Updates, Discussions, Assignments, Tests, Career and Technical Education, English, Fine Arts, Science, Social Studies, World Languages

e. Predictors: (Constant), Pretest, Updates, Assignments, Discussions, Tests, Career and Technical Education, English, Fine Arts, Health and PE, Social Studies.

f. Predictors: (Constant), Pretest, Updates, Discussions, Assignments, Tests, Career and Technical Education, English, Science, Social Studies, World Languages

Table 7
ANOVA for Posttest Scores by School Year and Course Length

School Year	Course Length	Model		Sum of Squares	df	Mean Square	F	Sig.
SY1415	Semester-Long	1	Regression	11584.117	1	11584.117	36.313	.000[b]
			Residual	179601.434	563	319.008		
		2	Regression	19637.010	5	3927.402	12.798	.000[c]
			Residual	171548.540	559	306.885		
		3	Regression	86246.067	10	8624.607	45.531	.000
			Residual	104939.483	554	189.421		
	Year-Long	1	Regression	18929.101	1	18929.101	69.714	.000[b]
			Residual	143637.475	529	271.526		
		2	Regression	41525.375	5	8305.075	36.022	.000[c]
			Residual	121041.201	525	230.555		
		3	Regression	45620.209	11	4147.292	18.405	.000
			Residual	116946.367	519	225.330		
SY1516	Semester-Long	1	Regression	8142.151	1	8142.151	62.583	.000[b]
			Residual	80662.771	620	130.101		
		2	Regression	10432.888	5	2086.578	16.400	.000[c]
			Residual	78372.034	616	127.227		
		3	Regression	15233.374	10	1523.337	12.651	.000
			Residual	73571.547	611	120.412		
	Year-Long	1	Regression	1394.800	1	1394.800	4.286	.039[b]
			Residual	152314.692	468	325.459		
		2	Regression	14021.368	5	2804.274	9.315	.000[c]
			Residual	139688.123	464	301.052		
		3	Regression	37190.750	10	3719.075	14.650	.000
			Residual	116518.742	459	253.853		

a. Dependent Variable: Posttest
b. Predictors: (Constant), Pretest
c. Predictors: (Constant), Pretest, Discussions, Tests, Assignments, Updates

To determine if the overall model had practical significance as well as statistical significance, effect sizes were calculated for each model, assessing the magnitude of an observed effect. Using the formula, $f^2 = R^2 / (1-R^2)$, the overall effect size was SY1415 SL (.82), SY1415 YL (.39), SY1516 SL (.21), and SY1516 YL (.29). The overall model for SY1415 SL and

SY1415 YL contained large effects. The overall model for SY1516 SL and SY1516 YL contained medium effects. Using the formula, $f^2 = R^2 / (1-R^2)$, the effect sizes for Model 1 (Pretest) were SY1415 SL (.06), SY1415 YL (.13), and SY1516 SL (.10). Model 1 contained small effects for SY1415 SL, SY1415 YL, and SY1516 SL. SY1516 YL was not statistically significant ($p > 0.001$) and also did not have an effect, which supports the study using $p < 0.001$ as the measure for significance. Using the formula $f^2 = R^2 / (1-R^2)$, the effect sizes for the R square change in Model 2 (Updates, Assignments, Tests, and Discussions) were, SY1415 SL (.04), SY1415 YL (.16), SY1516 SL (.03), and SY1516 YL (.09). The change in R square for Model 2 had a medium effect for SY1415 YL and a small effect for SY1415 SL, SY1516 SL, and SY1516 YL. The addition of LMS tools to the model was significant and had an effect. Using the formula $f^2 = R^2 / (1-R^2)$, the effect size for the R square change in Model 3 (curricular subject area dummy variables) was SY1415 SL (.53), SY1415 YL (.03), SY1516 SL (.06), and SY1516 YL (.18). The change in R square for Model 3 was a medium effect for SY1516 YL and a small effect for SY1516 SL. Not all curricular subject area variables were included in each of the school years and course lengths.

The overall model had statistically significant effects, and practical effects can be inferred, and a review of the beta weights in Table 8 showed that Model 2 (LMS tools) also had statistically significant coefficients that differed by school year and course length. Updates significantly contributed to all four models: SY1415 SL, $\beta = .17$, $t(559) = 3.68$, $p < .001$, 95% CI [0.072, 0.237], $.f^2 = .02$; SY1415 YL, $\beta = -.27$, $t(525) = -5.07$, $p < .001$, 95% CI [-0.221, -0.098], $.f^2 = .05$; SY1516 SL, $\beta = .13$, $t(616) = 3.38$, $p = .001$, 95% CI [0.059, 0.223], $.f^2 = .02$; SY1516 YL, $\beta = -.23$, $t(464) = -4.61$, $p < .001$, 95% CI [-0.280, - 0.112], $.f^2 = .05$. For updates, the semester-long courses were positively related to posttest scores, but year-long courses were negatively related. All four models for updates had a small effect size. Assignments significantly contributed predictive power for SY1516 YL, $\beta = .21$, $t(464) = 4.19$, $p < .001$, 95% CI [0.052, 0.144], $f^2 = .04$. Assignments were not significant a predictor for SY1415 SL, SY1516 SL or SY1415 YL. The LMS assignment tool for SY1516 YL had a small effect size and a positive relationship with posttest scores. Tests significantly contributed predictive power for SY1415 SL, $\beta = -.14$, $t(559) = -3.384$, $p < .001$, 95% CI [-0.303, -0.080], $f^2 = .02$, and were not significant for SY1415 YL, SY1516 SL, or SY1516 YL. Tests were found to have a negative relationship with posttest scores and a small effect size. Discussions significantly contributed predictive power for SY1415 YL, $\beta = .15$, $t(525) = 3.57$, $p < .001$, 95% CI 0[.141, 0.486], $f^2 = .02$, and were not significant for SY1415 SL, SY1516 SL, or SY1516 YL. Discussions were found to have a positive relationship with posttest scores and had a small effect size.

Table 8

Model 2 Coefficients for Posttest Scores by School Year and Course Length

				Std. Coef.			95.0% Confidence Interval for B		Corr.
School Year	Course Length	Model		Beta	t	Sig.	Lower Bound	Upper Bound	Partial
SY1415	Semester-Long	2	(Constant)		19.016	.000	54.398	66.930	
		2	Pretest	.243	6.004	.000	0.158	0.312	.246
		2	Updates	.168	3.683	.000	0.072	0.237	.154
		2	Assignments	.001	0.027	.978	-0.065	0.066	.001
		2	Tests	-.140	-3.384	.001	-0.303	-0.080	-.142
		2	Discussions	.013	0.292	.770	-0.212	0.286	.012
	Year-Long	2	(Constant)		26.942	.000	67.549	78.174	
		2	Pretest	.337	8.928	.000	0.229	0.358	.363
		2	Updates	-.266	-5.069	.000	-0.221	-0.098	-.216
		2	Assignments	-.068	-1.496	.135	-0.065	0.009	-.065
		2	Tests	-.003	-0.056	.955	-0.058	0.055	-.002
		2	Discussions	.145	3.567	.000	0.141	0.486	.154
SY1516	Semester-Long	2	(Constant)		36.283	.000	66.727	74.363	
		2	Pretest	.323	8.111	.000	0.139	0.228	.311
		2	Updates	.132	3.377	.001	0.059	0.223	.135
		2	Assignments	-.112	-2.863	.004	-0.065	-0.012	-.115
		2	Tests	-.012	-0.301	.763	-0.068	0.050	-.012
		2	Discussions	-.050	-1.258	.209	-0.326	0.071	-.051
	Year-Long	2	(Constant)		22.193	.000	69.889	83.468	
		2	Pretest	.058	1.299	.195	-0.025	0.123	.060
		2	Updates	-.227	-4.609	.000	-0.280	-0.112	-.209
		2	Assignments	.208	4.187	.000	0.052	0.144	.191
		2	Tests	-.033	-0.729	.467	-0.074	0.034	-.034
		2	Discussions	.129	2.773	.006	0.063	0.367	.128

Note. Standardized Coefficient is abbreviated Std. Coef. and Correlations is abbreviated Corr.

A review of the curricular subject area dummy variables for SY1415 showed that certain subject areas differed significantly from the math curricular subject area (Table 9). The LMS tools in Model 2 retained their significance when the curricular subject area variables were entered into Model 3. With the addition of curricular subject area, assignments and tests for SY1415 SL were also significant predictors of posttest scores: Assignments $\beta = -.21$, $t(554) = -4.16$, $p < .001$, 95% CI [-0.234, -0.084], $f^2 = .03$ and Tests $\beta = -.25$, $t(554) = -6.99$, $p < .001$, 95% CI [-0.443, -0.249], $f^2 = .09$. For SY1415 SL, Fine Arts $\beta = .37$, $t(554) = 6.12$, $p < .001$, 95% CI [11.93, 23.20], $f^2 = .07$; Health/PE $\beta = .45$, $t(554) = 6.36$, $p < .001$, 95% CI [15.50, 29.35], $f^2 = .07$; Social Studies (SS) $\beta = -.31$, $t(554) = -5.41$, $p < .001$, 95% CI [-16.98, -7.94], $f^2 = .05$, were significant predictors that differed from math. For SY1415 YL English $\beta = -.18$, $t(519) = -3.53$, $p < .001$, 95% CI [-16.06, -4.58], $f^2 = .02$ was a significant predictor that differed from math. Fine arts, health and PE, social studies, and science were small effects that significantly differed from the math curricular subject area comparison variable.

Table 9
Model 3 Coefficients for Posttest Scores for SY1415 by Course Length

				Std. Coef.			95.0% Confidence Interval for B		Corr.
School Year	Course Length	Model		Beta	t	Sig.	Lower Bound	Upper Bound	Partial
SY1415	Semester-Long	3	(Constant)		24.302	.000	66.435	78.119	
		3	Pretest	.099	2.898	.004	0.031	0.160	.122
		3	Updates	.361	8.802	.000	0.258	0.406	.350
		3	Assignments	-.207	-4.157	.000	-0.234	-0.084	-.174
		3	Tests	-.252	-6.988	.000	-0.443	-0.249	-.285
		3	Discussions	-.264	-6.033	.000	-1.031	-0.525	-.248
		3	CTE	-.007	-0.134	.894	-4.901	4.278	-.006
		3	English	-.069	-2.118	.035	-29.239	-1.100	-.090
		3	Fine Arts	.374	6.122	.000	11.929	23.201	.252
		3	Health/PE	.452	6.360	.000	15.496	29.345	.261
		3	Soc. Studies	-.307	-5.414	.000	-16.978	-7.938	-.224
	Year-Long	3	(Constant)		26.052	.000	70.156	81.599	
		3	Pretest	.360	8.721	.000	0.243	0.384	.358
		3	Updates	-.274	-4.933	.000	-0.229	-0.099	-.212
		3	Assignments	-.043	-0.853	.394	-0.059	0.023	-.037
		3	Tests	-.020	-0.375	.708	-0.076	0.051	-.016
		3	Discussions	.194	4.101	.000	0.218	0.618	.177
		3	CTE	-.073	-1.603	.110	-12.712	1.289	-.070
		3	English	-.180	-3.531	.000	-16.056	-4.576	-.153
		3	Fine Arts	-.007	-0.165	.869	-10.967	9.270	-.007
		3	Soc. Studies	-.093	-1.550	.122	-8.455	0.997	-.068
		3	Science	-.165	-3.043	.002	-12.990	-2.798	-.132
		3	World Lang.	-.112	-1.769	.077	-9.442	0.494	-.077

Note. Standardized Coefficient is abbreviated Std. Coef. and Correlations is abbreviated Corr.

A review of the curricular subject area dummy variables for SY1516 showed that certain subject areas differed significantly from the math curricular subject area (Table 10). When the curricular subject area variables were entered into Model 3, the LMS tools in Model 2 changed for the course lengths. For SY1516 SL, updates and assignments were no longer significant predictors. Discussions β = -.17, t(611) = -3.19, p = .001, 95% CI [-0.684, -0.163], f^2 = .02, was the only significant predictor and had a small effect size. For SY1516 YL, updates, assignments, and discussions retained their significant predictive power, but Tests, β = -.23, t(611) = -4.73, p < .001, 95% CI [-0.200, -0.082], f^2 = .05, were also a significant predictor and had a small effect size. For SY1516 SL, Fine Arts, β = .37, t(554) = 6.12, p < .001, 95% CI [11.93, 23.20], f^2 = .07, was a significant predictor that differed from math. For SY1516 YL, Career and Technical Education (CTE), β = .17, t(459) = 3.44, p = .001, 95% CI [5.69, 20.90], f^2 = .03 and Science β = -.40, t(459) = -6.42, p < .001, 95% CI [-24.23, -12.87], f^2 = .09, were significant predictors that differed from math. The effect sizes for fine arts, career and technical education, and science were small.

Table 10
Model 3 Coefficients for Posttest Scores for SY1516 by Course Length

School Year	Course Length	Model		Std. Coef. Beta	t	Sig.	95.0% Confidence Interval for B Lower Bound	Upper Bound	Corr. Partial
SY1516	Semester-Long	3	(Constant)		27.508	.000	68.248	78.742	
		3	Pretest	.302	7.352	.000	0.126	0.217	.285
		3	Updates	.060	1.282	.200	-0.034	0.163	.052
		3	Assignments	.042	0.888	.375	-0.017	0.046	.036
		3	Tests	-.071	-1.686	.092	-0.114	0.009	-.068
		3	Discussions	-.165	-3.190	.001	-0.684	-0.163	-.128
		3	CTE	-.108	-1.271	.204	-7.321	1.568	-.051
		3	English	-.020	-0.490	.624	-13.143	7.892	-.020
		3	Fine Arts	.220	2.908	.004	2.335	12.055	.117
		3	Health/PE	-.131	-1.564	.118	-8.296	0.940	-.063
		3	Soc. Studies	.031	0.389	.697	-3.385	5.057	.016
	Year-Long	3	(Constant)		24.648	.000	82.001	96.209	
		3	Pretest	.102	2.256	.025	0.011	0.159	.105
		3	Updates	-.278	-5.535	.000	-0.326	-0.155	-.250
		3	Assignments	.123	2.311	.021	0.009	0.108	.107
		3	Tests	-.232	-4.726	.000	-0.200	-0.082	-.215
		3	Discussions	.181	3.546	.000	0.134	0.469	.163
		3	CTE	.171	3.436	.001	5.689	20.895	.158
		3	English	-.007	-0.114	.909	-8.720	7.762	-.005
		3	Soc.Studies	-.066	-0.980	.327	-8.553	2.860	-.046
		3	Science	-.398	-6.418	.000	-24.233	-12.871	-.287
		3	World Lang.	.033	0.477	.634	-4.053	6.650	.022

Note. Standardized Coefficient is abbreviated Std. Coef. and Correlations is abbreviated Corr.

To summarize the results for Research Question 2, the overall model significantly predicted posttest scores for SY1415 SL, $R^2 = .45$, $R^2_{adj} = .44$, $F(10, 554) = 45.53$, $p < .001$; SY1415 YL, $R^2 = .28$, $R^2_{adj} = .27$, $F(11, 519) = 18.41$, $p < .001$; SY1516 SL, $R^2 = .17$, $R^2_{adj} = .16$,

$F(10, 611) = 12.65$, $p < .001$; SY1516 YL, $R^2 = .24$, $R^2_{adj} = .23$, $F(10, 459) = 14.65$, $p < .001$. The lowest overall variance accounted for was 17% for SY1516 SL and the highest variance was 45% for SY1415 SL. The variance accounted for by the control variable Pretest (Model 1) out of the total variance was SY1415 SL, 6.1% of 45%; SY1415 YL 11.6% of 27%: SY1516 SL 9.2% of 17%; and SY1516 YL 0.7% of 25%. The inclusion of the LMS tools (Model 2) added 4.2% variance explained to SY1415 SL, 13.9% to SY1415 YL, 2.6% to SY1516 SL, and 8.2% to SY1516 YL. The inclusion of the curricular subject areas (Model 3) added 34.8% variance explained to SY1415 SL, 2.5% to SY1415 YL, 5.4% to SY1516 SL, and 15.1% to SY1516 YL. The effect size (f^2) for the R Square Change (ΔR^2) in models for SY1415 SL was small (Model 1 = .06, Model 2 = .04,) and large (Model 3 = .56). The effect size (f^2) for the R Square Change (ΔR^2) in models for SY1415 YL was small (Model 1 = .13, Model 3 = .03) and medium (Model 2 = .16). The effect size (f^2) for the R Square Change (ΔR^2) in models for SY1516 SL was small (Model 1 = .10, Model 2 = .03, and Model 3 = .06). The effect size (f^2) for the R Square Change (ΔR^2) in models for SY1516 YL was no effect (Model 1 = .009), small (Model 2 = .09), and medium (Model 3 = .18).

Updates, assignments, tests, and discussions were significant predictors for posttest scores and had small effect sizes. Course length did effect the LMS tool predictors in terms of variance explained and effect size. The LMS tool variance explained by course length ranged from 2.6% to13.9% and from small to medium effect size. The curricular subject areas had significant differences from the math comparison group and had small effect sizes. The significant differences in the predictive power of curricular subject areas is further analyzed in Research Question 3.

Research Question 3

RQ3: To what extent does curricular subject area in addition to the frequency of LMS tool use affect the prediction of student achievement and student learning in online secondary courses?

A univariate general linear model (GLM) analysis of variance (ANOVA) was conducted to determine if the independent variable curricular subject area had an effect on semester final grades and posttest scores. An ANOVA was run for semester final grades and for posttest scores using curricular subject area as the fixed factor. Using the GLM ANOVA option allowed for the calculation of effect sizes and was converted into f^2 effect sizes for comparison. Based on the results, a hierarchical multiple regression was conducted to determine the overall effect of curricular subject area on student achievement and student learning. The dependent variable semester final grades was used for student achievement and the posttest scores variable was used for student learning. The control variable (Pretest) was entered into Block 1 of the regression equation. The LMS tools of updates, assignments, tests, and discussion boards were entered into Block 2.

The previous research questions showed that the curricular subject areas were significantly different from the math comparison group in their predictive power. In order to evaluate the predictive power of each curricular subject area, the dataset was split using the curricular subject area variable. The curricular subject area variable was nominal and identified each of the eight curricular subject areas (career and technical education, English, fine arts, health and PE, math, science, social studies, and world languages). The dataset for semester final grades contained only semester-long data, but the dataset for posttest scores contained semester-long and year-long data. The dataset for posttest scores required a further split by the course length variable, labeled Semester-Long and Year-Long. The entire SPSS output is available upon request, reference Appendix C.

Semester Final Grade Regression Assumption Analysis. The following assumptions for a regression equation were analyzed: linearity, normality, homoscedasticity, multicollinearity, independent of errors/autocorrelation, and outliers/influential cases. An analysis of the Mahalanobis distance was used to identify any outliers, seven cases were identified using the critical Chi-Square value of 20.52, $p = .001$. The cases had standardized residuals $< \pm 2$, which did not indicate high influence. The standardized DFBETAs for pretest, updates, assignments, tests, and discussions were also assessed. The DFBETA range minimum (-0.09) and maximum (0.16) were within than the accepted maximum > 2 and minimum < -2. It was concluded that the outliers were not influential cases within the 3,043 analyzed cases that were split by curricular subject area.

To assess whether multicollinearity was present, the collinearity statistics of tolerance and variance inflation factor (VIF) were used. A tolerance value of < .10 and a VIF of > 5 may indicate high multicollinearity (Mertler & Vannatta, 2005). The lowest tolerance values and highest VIF in Model 2 was the curricular subject area of career and technical education. For the coefficient of updates, tolerance (.15) was not a concern but VIF (6.7) was a concern. For the coefficient of discussions, tolerance (.14) was not a concern, but VIF (7.1) was a concern. The correlation between updates and discussions was reviewed and showed that career and technical education were highly correlated, $r = .92$. The Pearson correlation for updates and discussions for the other curricular subject areas were English (.67), fine arts (.46), health and PE (-.21), math (.18), science (-.04), social studies (-.50), and world languages (.01). Only career and technical education had a strong linear relationship between updates and discussions, which added to the value of VIF. For equal comparison of R^2, updates and discussion boards remained in the analysis for career and technical education. To verify that the residual terms were uncorrelated, a Durbin-Watson test was conducted. The data were sorted by curricular subject area during the split process in SPSS. The Durbin-Watson values for the curricular subject areas were career and technical education (1.86), English (1.65), fine arts (2.127), health and PE (2.06), math (1.85), science (1.83), social studies (1.92), and world languages (1.84). The values were very close to the value of 2 and none was less than 1. The data met the assumption of independent errors and did not have autocorrelation.

The assumptions of normality, homoscedasticity, and linearity were evaluated by graph interpretation. To test normality, standardized residual histograms with normal fit line and normal P-P plots with goodness of fit lines were generated. The distribution for each curricular subject area was very close to the normal fit line. The majority of values for the standardized residual were within ± 3. The normal P-P plots had points that followed the goodness of fit line. The data were normally distributed and the assumption of normality was met. A scatterplot of the standardized residuals by standardized predicted values was created to test the assumption of homoscedasticity and linearity. The scatterplots in Figure 12 and Figure 13 showed that there was not a pattern to the residuals plotted against the fitted values. A slight tapering of the positive values was visible, which indicated some heteroscedasticity. Linearity was also confirmed, as the plot was roughly rectangular within +3 and -3 standard deviations.

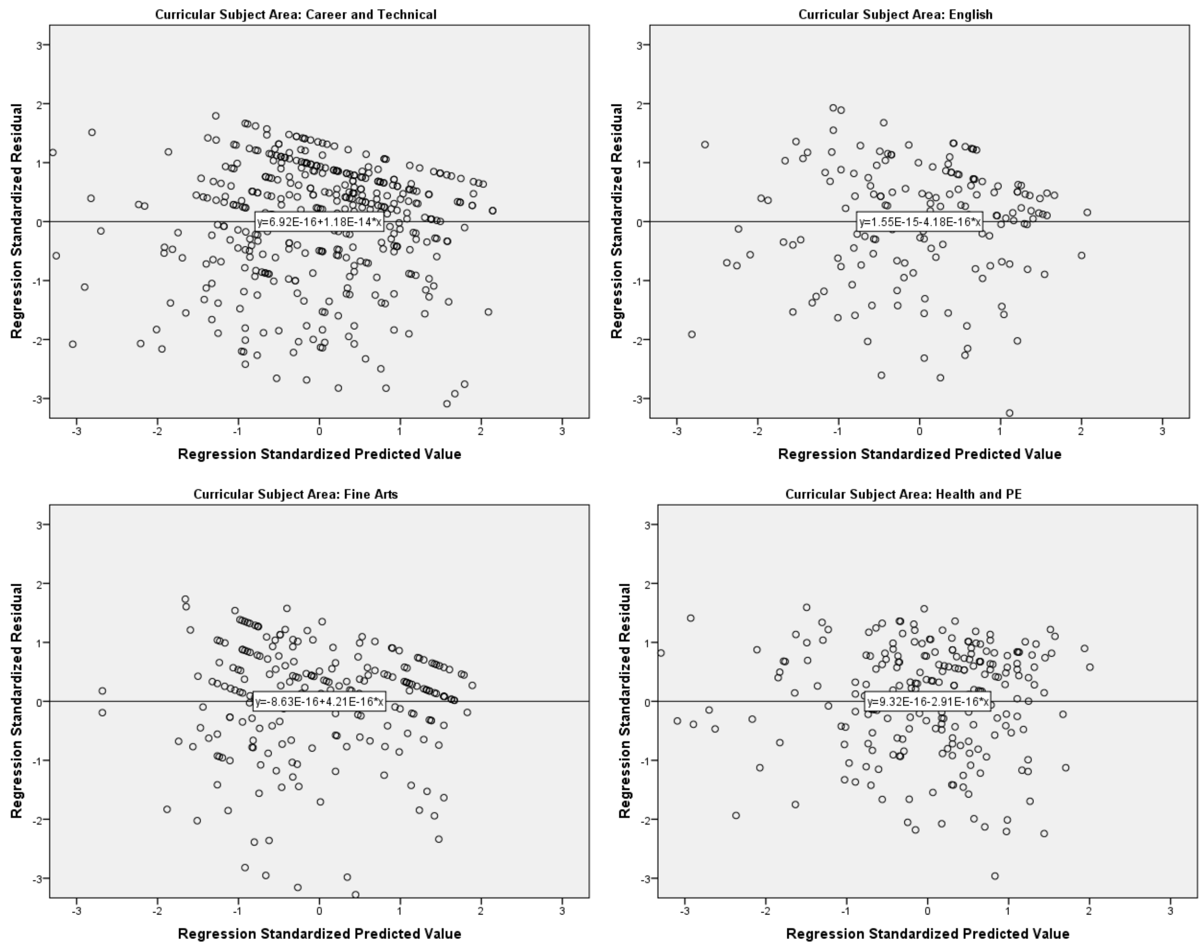

Figure 12. Scatterplot of standardized residual values and standardized predicted values with a linear fit line for career and technical education, English, fine arts, and health and PE.

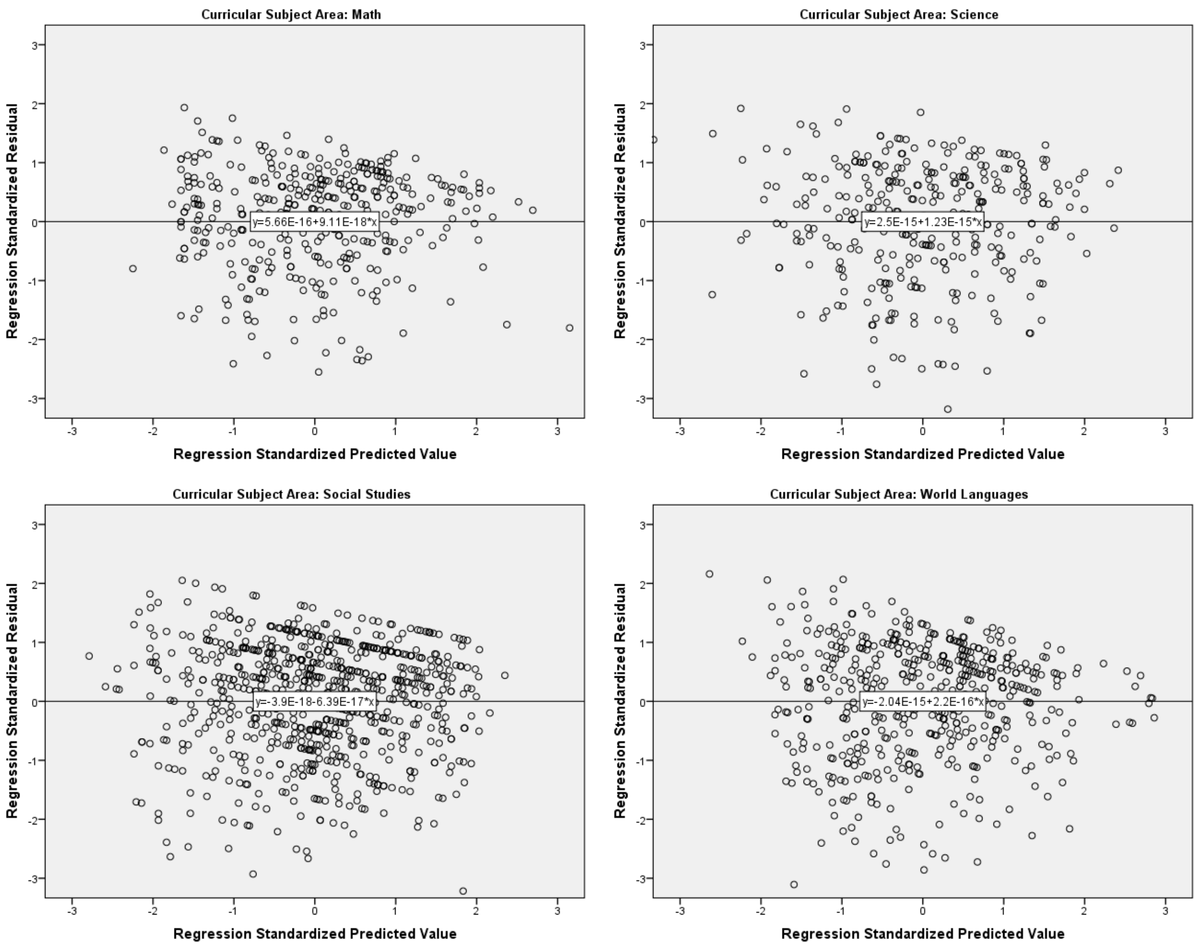

Figure 13. Scatterplot of standardized residual values and standardized predicted values with a linear fit line for math, science, social studies, and world languages.

Posttest Score Regression Assumption Analysis. The following assumptions for a regression equation were analyzed: linearity, normality, homoscedasticity, multicollinearity, independent of errors/autocorrelation, and outliers/influential cases. An analysis of the Mahalanobis distance was used to identify any outliers, using the critical Chi-Square value of 20.52, p = .001. Nine cases were identified as above the critical Chi-Square value. Of the nine cases, only one case had a standardized residual > ± 2. This case had a Cook's distance of 0.19, which indicated that there was not high influence. The standardized DFBETAs for pretest, updates, assignments, tests, and discussions were also assessed. The range minimum (-1.12) and maximum (0.92) were both less than the accepted maximum > 2 and minimum < -2. It can be concluded that the outliers were not influential cases within the 2188 analyzed cases that were split by curricular subject area and course length.

The collinearity statistics of tolerance and variance inflation factor (VIF) were calculated to determine the presence of multicollinearity. A tolerance value of < .10 and a VIF of > 5 may indicate high multicollinearity (Mertler & Vannatta, 2005). The lowest tolerance values and highest VIF in Model 2 were the curricular subject area career and technical education semester-long. The tolerance for updates (.11) and assignments (.11) were close to high multicollinearity, but the VIF for updates (8.76) and assignments (8.89) was a concern. A review of the correlations for career and technical education SL revealed that updates and discussions were highly correlated, $r = .94$. Only career and technical education had a strong linear relationship between updates and discussions. The next-highest Pearson correlation ($r = -.71$) was math YL, which displayed a negative relationship for assignments and tests. Updates in social studies YL were highly correlated, with assignments ($r = .79$), tests ($r = .70$) and discussions ($r = -.72$). For equal comparison of R^2, the highly correlated LMS tools were not removed for individual curricular subject areas. To verify that the residual terms were uncorrelated, a Durbin-Watson test was conducted. The data were sorted by curricular subject area, then by course length during the split process in SPSS. The Durbin-Watson value closest to 3 or 1 was English SL (2.88), which displayed a strong negative autocorrelation. English SL only contained 9 cases, which was below the necessary sample size of 63 cases for power of .95, large effect size, and alpha of .05, with 5 predictors. The remaining data met the assumption of independent errors and did not have autocorrelation.

The assumptions of normality, homoscedasticity, and linearity were again evaluated by graph interpretation. To test normality, standardized residual histograms with normal fit line and normal P-P plots with goodness of fit lines were generated. The distribution for English SL and fine arts YL did not appear normal and also contained sample sizes below the necessary sample size of 63 cases. The remaining curricular subject area distributions were very close to the normal fit line. The majority of the values for the standardized residual were within ± 3. The normal P-P plots also confirmed that English SL and fine arts YL did not follow the goodness of fit line. The normal P-P plots for the remaining curricular subject areas were very close to the goodness of fit line. Other than English SL and fine arts YL, the data were normally distributed and the assumption of normality was met. To test the assumption of homoscedasticity and linearity, a scatterplot of the standardized residuals by standardized predicted values was generated. The scatterplots in *Figure 14* showed heteroscedasticity through vertically oriented values for career and technical education YL and English SL. Fine arts YL had only a few cases, but there was a noticeable heteroscedastic taper for positive predicted values. Social studies SL also had vertically aligned values and some clustering of values, which created a noticeable pattern that violated homoscedasticity. All other curricular subject areas and course lengths did not violate the assumption of homoscedasticity and were included in the regression analyses. Linearity was confirmed, as the plots were roughly rectangular within +3 and -3 standard deviations. The heteroscedastic curricular subject areas of career and technical education YL, English SL, fine arts YL, and social studies SL were not reported in the regression analysis.

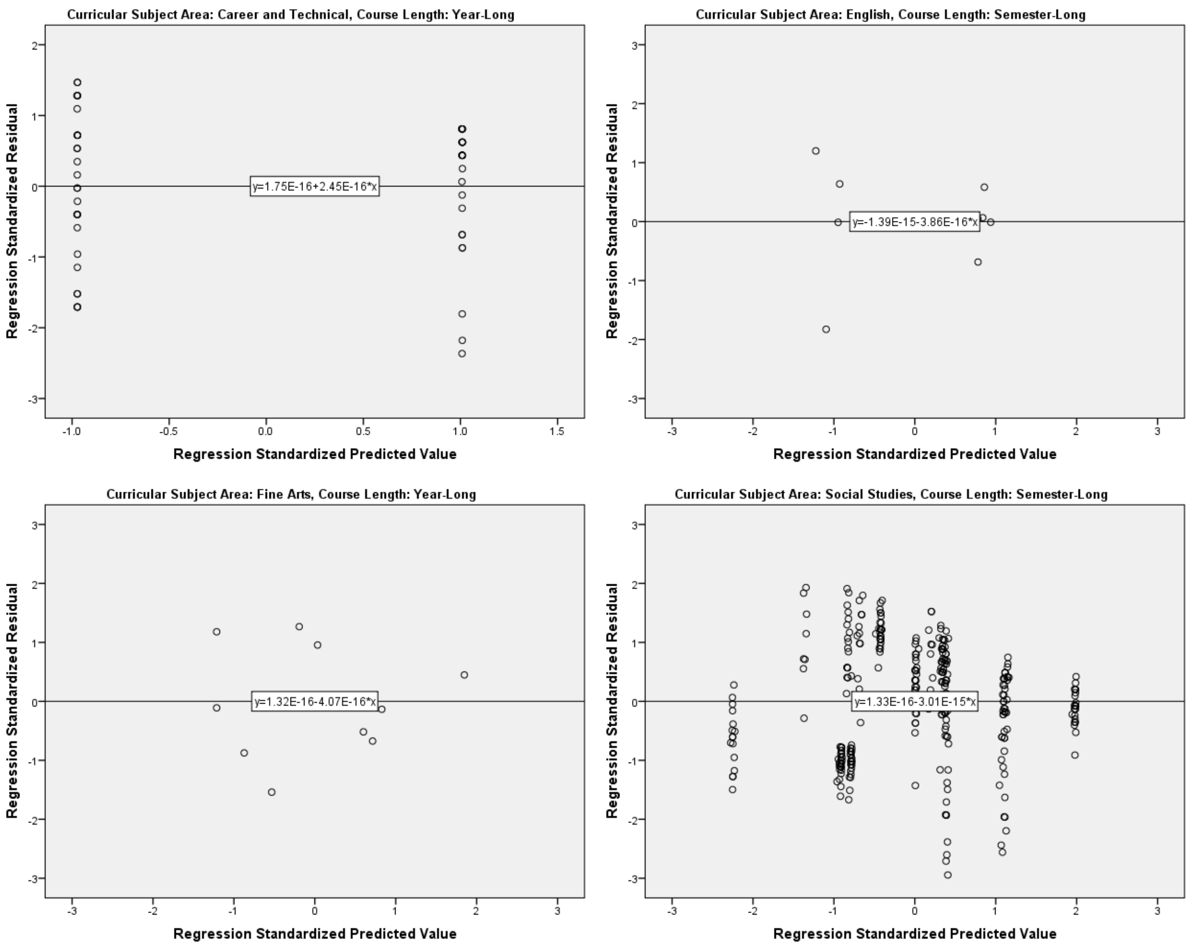

Figure 14. Scatterplot of standardized residuals by standardized predicted value for career and technical education YL, English SL, fine arts YL, social studies SL.

Research Question 3 Summary

To determine if curricular subject area had a significant effect on semester final grades and posttest scores, a univariate GLM ANOVA was conducted. Levene's test was used to determine the null hypothesis that the population of curricular subject areas had equal variances. Levene's test for semester final grades was significant ($F = 7.09$, $p < .001$), which indicated unequal variances and a rejection of the null hypothesis. Levene's test for posttest scores was also significant ($F = 29.53$, $p < .001$), which indicated unequal variances and a rejection of the null hypothesis. The tests of between-subjects effects was significant for semester final grades,

$R^2 = .03$, $R^2_{adj} = .02$, $F(7, 3035) = 11.38$, $p < .001$. The tests of between-subjects effects was also significant for posttest scores, $R^2 = .06$, $R^2_{adj} = .05$, $F(7, 2180) = 18.64$, $p < .001$. The results indicated that curricular subject area without any other predictors explained 3% of the variance for semester final grades and 6% of the variance for posttest scores. The effect sizes were small for semester final grades ($f^2 = .02$) and posttest scores ($f^2 = .06$). Each curricular subject area contained a significant pairwise comparison. To reduce the risk of Type I errors (false-positive), the Bonferroni correction was used to adjust the p values, and were found to be significant at $p < .001$. The entire SPSS output for the univariate analysis of variance of semester final grades and posttest scores is available upon request, reference Appendix D. The results of the analysis indicated significantly different variance by curricular subject area. A hierarchical regression for pretest and LMS tools required splitting the dataset by curricular subject area.

A hierarchical multiple regression was conducted to determine the accuracy of the independent variables in predicting posttest scores. The control variable of pretest scores [Pretest] was entered into Block 1. The independent variables frequency of updates [Updates], frequency of assignments [Assignments], frequency of tests [Tests], and frequency of discussion boards [Discussions] were entered into Block 2. The curricular subject area dummy variables were not used in Block 3, but the dataset was split by the nominal variable Curricular Subject Area. The independent variables were therefore compared by their curricular subject area category (career and technical education, English, fine arts, health and PE, math, science, social studies, and world languages). The posttest dataset contained both semester-long and year-long values and required an additional split by course length.

Semester Final Grades Regression. The regression results in Table 11 and Table 12 indicated that the overall model split by curricular subject area significantly predicted semester final grades for career and technical education $R^2 = .11$, $R^2_{adj} = .10$, $F(5, 409) = 10.19$, $p < .001$; English, $R^2 = .14$, $R^2_{adj} = .12$, $F(5, 160) = 5.39$, $p < .001$; fine arts, $R^2 = .21$, $R^2_{adj} = .20$, $F(5, 220) = 12.01$, $p < .001$; math, $R^2 = .08$, $R^2_{adj} = .07$, $F(5, 385) = 7.08$, $p < .001$; social studies, $R^2 = .08$, $R^2_{adj} = .07$, $F(5, 766) = 12.82$, $p < .001$; and world languages, $R^2 = .17$, $R^2_{adj} = .16$, $F(5, 503) = 20.00$, $p < .001$. The pretest control variable in Model 1 significantly ($p < .001$) predicted semester final grades in English, fine arts, health and PE, math, social studies, and world languages and ranged from 5% to 14% variance predicted. The addition of the LMS tools (Updates, Assignments, Tests, and Discussions) in Model 2 significantly added predictive power for career and technical education, $\Delta R^2 = .10$, $\Delta F(4, 409) = 11.18$, $p < .001$, $f^2 = .1$; fine arts, $\Delta R^2 = .07$, $\Delta F(4, 160) = 5.00$, $p = .001$, $f^2 = .02$; and world languages, $\Delta R^2 = .07$, $\Delta F(4, 503) = 9.86$, $p < .001$, $f^2 = .08$. Model 2 (LMS tools) was not significant for English, health and PE, math, science, and social studies. The effect size for the R Square Change for Model 2 was small. The LMS tools added 2% to 10% predictive power to the model when split by curricular subject area.

Table 11
Model Summary for Semester Final Grade[c] by Curricular Subject Area

Curricular Subject Area	Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics: R Square Change	F Change	df1	df2	Sig. F Change
Career and Technical	1	.117[a]	.014	.011	10.262	.014	5.695	1	413	.017
	2	.333[b]	.111	.100	9.791	.097	11.176	4	409	.000
English	1	.350[a]	.122	.117	7.917	.122	22.881	1	164	.000
	2	.380[b]	.144	.117	7.916	.022	1.018	4	160	.400
Fine Arts	1	.378[a]	.143	.139	8.435	.143	37.356	1	224	.000
	2	.463[b]	.214	.196	8.149	.071	5.000	4	220	.001
Health and PE	1	.265[a]	.070	.066	10.011	.070	18.043	1	239	.000
	2	.281[b]	.079	.059	10.048	.009	0.560	4	235	.692
Math	1	.232[a]	.054	.051	11.422	.054	22.111	1	389	.000
	2	.290[b]	.084	.072	11.295	.030	3.202	4	385	.013
Science	1	.141[a]	.020	.017	8.080	.020	6.491	1	321	.011
	2	.196[b]	.038	.023	8.054	.019	1.529	4	317	.193
Social Studies	1	.242[a]	.059	.058	8.735	.059	48.081	1	770	.000
	2	.278[b]	.077	.071	8.672	.018	3.832	4	766	.004
World Languages	1	.317[a]	.100	.099	9.690	.100	56.575	1	507	.000
	2	.407[b]	.166	.158	9.368	.065	9.863	4	503	.000

a. Predictors: (Constant), Pretest

b. Predictors: (Constant), Pretest, Updates, Assignments, Updates, Tests, Discussions

c. Dependent Variable: Semester Final Grade

Table 12
ANOVA[a] Results for Semester Final Grades by Curricular Subject Area

Curricular Subject Area	Model		Sum of Squares	df	Mean Square	F	Sig.
Career and Technical	1	Regression	599.776	1	599.776	5.695	.017[b]
		Residual	43493.081	413	105.310		
	2	Regression	4885.296	5	977.059	10.192	.000[c]
		Residual	39207.562	409	95.862		
English	1	Regression	1434.288	1	1434.288	22.881	.000[b]
		Residual	10280.242	164	62.684		
	2	Regression	1689.527	5	337.905	5.393	.000[c]
		Residual	10025.004	160	62.656		
Fine Arts	1	Regression	2657.594	1	2657.594	37.356	.000[b]
		Residual	15935.985	224	71.143		
	2	Regression	3985.606	5	797.121	12.005	.000[c]
		Residual	14607.973	220	66.400		
Health and PE	1	Regression	1808.204	1	1808.204	18.043	.000[b]
		Residual	23952.210	239	100.218		
	2	Regression	2034.230	5	406.846	4.030	.002[c]
		Residual	23726.185	235	100.962		
Math	1	Regression	2884.688	1	2884.688	22.111	.000[b]
		Residual	50749.700	389	130.462		
	2	Regression	4518.678	5	903.736	7.084	.000[c]
		Residual	49115.711	385	127.573		
Science	1	Regression	423.784	1	423.784	6.491	.011[b]
		Residual	20958.012	321	65.290		
	2	Regression	820.555	5	164.111	2.530	.029[c]
		Residual	20561.241	317	64.862		
Social Studies	1	Regression	3668.686	1	3668.686	48.081	.000[b]
		Residual	58753.080	770	76.303		
	2	Regression	4821.166	5	964.233	12.823	.000[c]
		Residual	57600.599	766	75.197		
World Languages	1	Regression	5311.942	1	5311.942	56.575	.000[b]
		Residual	47603.319	507	93.892		
	2	Regression	8774.128	5	1754.826	19.997	.000[c]
		Residual	44141.133	503	87.756		

a. Dependent Variable: Semester Final Grade

b. Predictors: (Constant), Pretest

c. Predictors: (Constant), Pretest, Assignments, Updates, Tests, Discussions

Posttest Score Regression. The heteroscedastic curricular subject areas of career and technical education YL, English SL, fine arts YL, and social studies SL are not reported in the regression results. The regression results in Table 13, Table 14, and Table 15 indicated that the overall model split by curricular subject area and course length significantly predicted posttest scores for: career and technical education SL, $R^2 = .04$, $R^2_{adj} = .03$, $F(5, 306) = 6.74$, $p < .001$; English YL, $R^2 = .31$, $R^2_{adj} = .27$, $F(5, 87) = 7.95$, $p < .001$; fine arts SL, $R^2 = .39$, $R^2_{adj} = .38$, $F(5, 200) = 25.64$, $p < .001$; health and PE SL, $R^2 = .12$ $R^2_{adj} = .10$, $F(5, 235) = 6.24$, $p < .001$; math SL, $R^2 = .33$, $R^2_{adj} = .29$, $F(5, 91) = 8.95$, $p < .001$; science YL, $R^2 = .30$, $R^2_{adj} = .28$, $F(5, 166) = 14.32$, $p < .001$; social studies YL, $R^2 = .45$, $R^2_{adj} = .44$, $F(5, 234) = 38.21$, $p < .001$; and world languages, $R^2 = .30$, $R^2_{adj} = .29$, $F(5, 270) = 23.22$, $p < .001$. The pretest control variable in Model 1 significantly ($p < .001$) predicted the variance in posttest scores for career and technical SL (4%), English YL (12%), fine arts SL (22%), health and PE (7%), math SL (18%), social studies YL (5%), and world languages YL (14%). The pretest control variable did not significantly predict the variance for math YL ($p = .006$) or science YL ($p = .15$).

The addition of the LMS tools (Updates, Assignments, Tests, and Discussions) in Model 2 significantly added predictive power for career and technical education SL, $\Delta R^2 = .06$, $\Delta F(4, 306) = 5.44$, $p < .001$, $f^2 = .06$; English YL, $\Delta R^2 = .20$, $\Delta F(4, 87) = 6.24$, $p < .001$, $f^2 = .25$; fine arts SL, $\Delta R^2 = .17$, $\Delta F(4, 200) = 13.71$, $p < .001$, $f^2 = .20$; math SL, $\Delta R^2 = .15$, $\Delta F(4, 91) = 4.99$, $p = .001$, $f^2 = .18$; science YL, $\Delta R^2 = .29$, $\Delta F(4, 166) = 17.17$, $p < .001$, $f^2 = .41$; social studies YL, $\Delta R^2 = .39$, $\Delta F(4, 234) = 41.70$, $p < .001$, $f^2 = .64$; and world languages YL, $\Delta R^2 = .16$, $\Delta F(4, 270) = 15.12$, $p < .001$, $f^2 = .19$. Adding the LMS tools was not significant for math YL ($p = .07$) or health and PE ($p = .01$). The effect size for the R Square Change for Model 2 was small for career and technical education (.06). The effect size for the R Square Change for Model 2 was medium for English YL (.25), fine arts SL (.20), math SL (.18), and world languages YL (.19). The effect size for the R Square Change for Model 2 was large for science YL (.41) and social studies YL (.64). The LMS tools added 5% to 39% predictive power to the model when split by curricular subject area and course length. For large effects, the LMS tools predicted 29% of the variance for science YL and 39% of the variance for social studies YL.

Table 13
Model Summary[c] of Posttest Scores by Curricular Subject Area and Course Length

Curricular Subject Area	Course Length	Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics: R Square Change	F Change	df1	df2	Sig. F Change
Career and Technical	Semester-Long	1	.188[a]	.035	.032	11.936	.035	11.306	1	310	.001
		2	.315[b]	.099	.085	11.608	.064	5.441	4	306	.000
English	Year-Long	1	.342[a]	.117	.107	14.233	.117	12.043	1	91	.001
		2	.560[b]	.314	.274	12.832	.197	6.238	4	87	.000
Fine Arts	Semester-Long	1	.473[a]	.223	.220	8.544	.223	58.713	1	204	.000
		2	.625[b]	.391	.375	7.645	.167	13.712	4	200	.000
Health and PE	Semester-Long	1	.262[a]	.069	.065	10.211	.069	17.615	1	239	.000
		2	.342[b]	.117	.098	10.025	.049	3.236	4	235	.013
Math	Semester-Long	1	.427[a]	.183	.174	16.720	.183	21.227	1	95	.000
		2	.574[b]	.330	.293	15.471	.147	4.989	4	91	.001
	Year-Long	1	.221[a]	.049	.043	16.318	.049	7.858	1	153	.006
		2	.319[b]	.102	.071	16.070	.053	2.189	4	149	.073
Science	Year-Long	1	.111[a]	.012	.006	18.567	.012	2.113	1	170	.148
		2	.549[b]	.301	.280	15.803	.289	17.169	4	166	.000
Social Studies	Year-Long	1	.239[a]	.057	.053	17.413	.057	14.388	1	238	.000
		2	.670[b]	.449	.438	13.418	.392	41.702	4	234	.000
World Languages	Year-Long	1	.380[a]	.144	.141	15.649	.144	46.118	1	274	.000
		2	.548[b]	.301	.288	14.249	.157	15.120	4	270	.000

a. Predictors: (Constant), Pretest
b. Predictors: (Constant), Pretest, Tests, Assignments, Updates, Discussions
c. Dependent Variable: Posttest

Table 14
ANOVA[a] Results for Posttest Scores for Career and Technical Education, English, Fine Arts, and Health and PE split by course length

Curricular Subject Area	Course Length	Model		Sum of Squares	df	Mean Square	F	Sig.
Career and Technical	Semester-Long	1	Regression	1610.779	1	1610.779	11.306	.001[b]
			Residual	44166.193	310	142.472		
			Total	45776.971	311			
		2	Regression	4543.250	5	908.650	6.743	.000[c]
			Residual	41233.721	306	134.751		
			Total	45776.971	311			
			Total	26593.745	54			
English	Year-Long	1	Regression	2439.662	1	2439.662	12.043	.001[b]
			Residual	18435.327	91	202.586		
			Total	20874.989	92			
		2	Regression	6548.737	5	1309.747	7.954	.000[c]
			Residual	14326.252	87	164.670		
			Total	20874.989	92			
Fine Arts	Semester-Long	1	Regression	4286.410	1	4286.410	58.713	.000[b]
			Residual	14893.304	204	73.006		
			Total	19179.714	205			
		2	Regression	7491.645	5	1498.329	25.639	.000[c]
			Residual	11688.068	200	58.440		
			Total	19179.714	205			
Health and PE	Semester-Long	1	Regression	1836.744	1	1836.744	17.615	.000[b]
			Residual	24920.294	239	104.269		
			Total	26757.037	240			
		2	Regression	3137.646	5	627.529	6.244	.000[c]
			Residual	23619.392	235	100.508		
			Total	26757.037	240			

a. Dependent Variable: Posttest

b. Predictors: (Constant), Pretest

c. Predictors: (Constant), Pretest, Tests, Assignments, Updates, Discussions

Table 15
ANOVA[a] Results for Posttest Scores for Math, Science, Social Studies, and World Language split by course length

Curricular Subject Area	Course Length	Model		Sum of Squares	df	Mean Square	F	Sig.
Math	Semester-Long	1	Regression	5934.090	1	5934.090	21.227	.000[b]
			Residual	26558.157	95	279.560		
			Total	32492.247	96			
		2	Regression	10710.930	5	2142.186	8.950	.000[c]
			Residual	21781.317	91	239.355		
			Total	32492.247	96			
	Year-Long	1	Regression	2092.409	1	2092.409	7.858	.006[b]
			Residual	40738.133	153	266.262		
			Total	42830.542	154			
		2	Regression	4353.511	5	870.702	3.372	.006[c]
			Residual	38477.031	149	258.235		
			Total	42830.542	154			
Science	Year-Long	1	Regression	728.587	1	728.587	2.113	.148[b]
			Residual	58604.924	170	344.735		
			Total	59333.512	171			
		2	Regression	17878.653	5	3575.731	14.318	.000[c]
			Residual	41454.859	166	249.728		
			Total	59333.512	171			
Social Studies	Year-Long	1	Regression	4362.497	1	4362.497	14.388	.000[b]
			Residual	72161.565	238	303.200		
			Total	76524.063	239			
		2	Regression	34394.490	5	6878.898	38.207	.000[c]
			Residual	42129.572	234	180.041		
			Total	76524.063	239			
World Languages	Year-Long	1	Regression	11293.868	1	11293.868	46.118	.000[b]
			Residual	67099.944	274	244.890		
			Total	78393.812	275			
		2	Regression	23573.476	5	4714.695	23.221	.000[c]
			Residual	54820.336	270	203.038		
			Total	78393.812	275			

a. Dependent Variable: Posttest

b. Predictors: (Constant), Pretest

c. Predictors: (Constant), Pretest, Tests, Assignments, Updates, Discussions

The standardized predicted values when plotted against the dependents actual values showed that the curricular subject areas varied in the amount of variance predicted. The semester final grades scatterplots displayed in Figure 15 and Figure 16 visually show how curricular subject areas differed in their predictive power and linear fit.

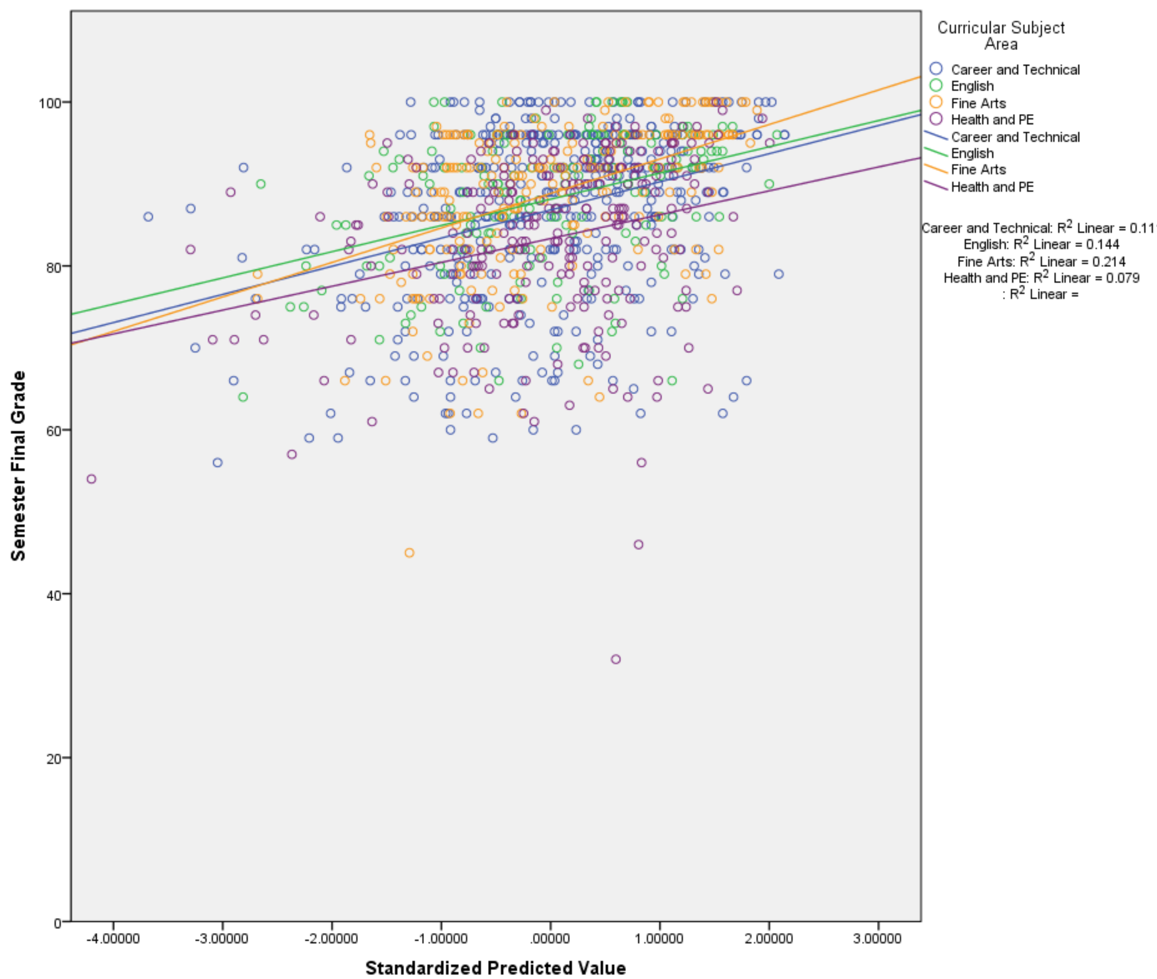

Figure 15. Scatterplot of semester final grades and standardized predicted values for career and technical, fine arts, health and PE curricular subject areas with a linear fit line.

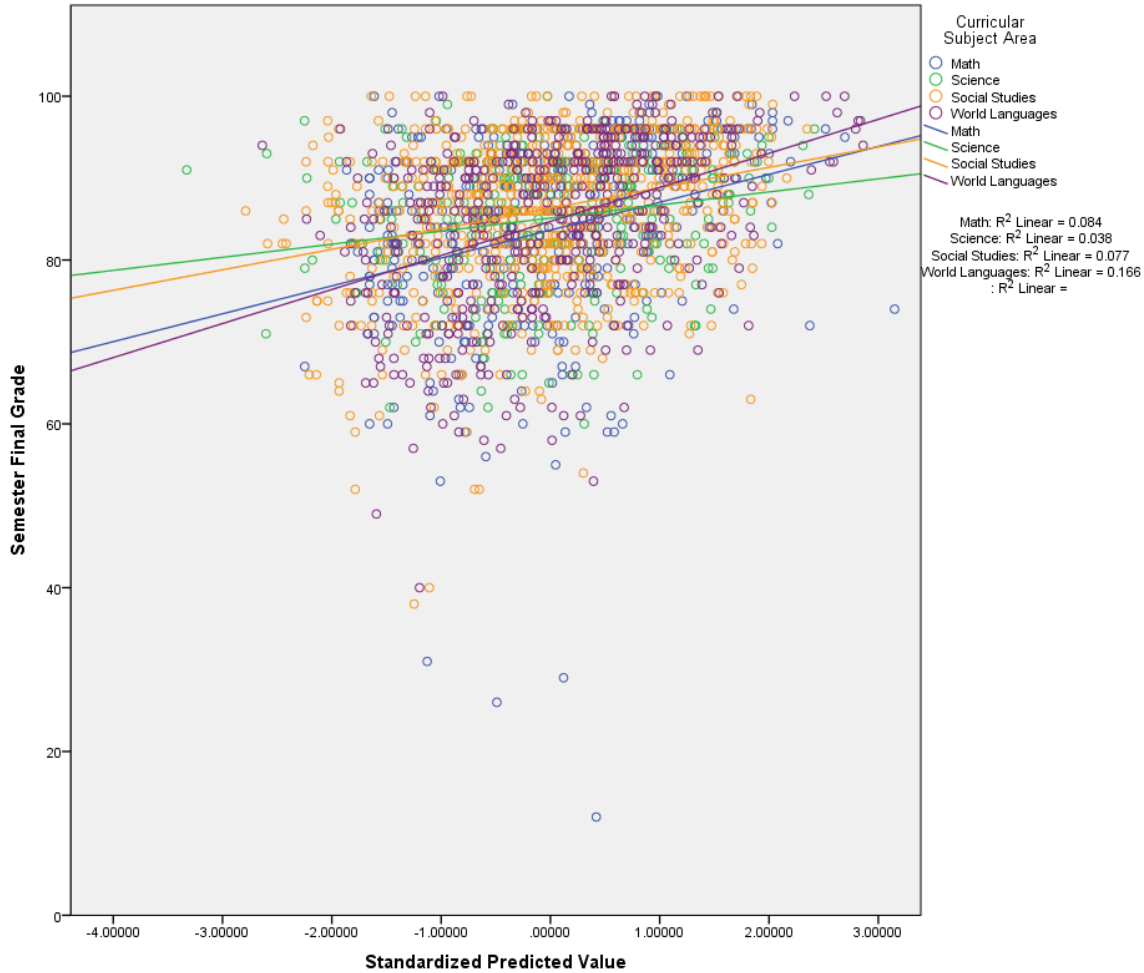

Figure 16. Scatterplot of semester final grades and standardized predicted values for math, science, social studies and world languages curricular subject areas with a linear fit line.

Curricular subject area was split by course length to graph posttest scores. Figure 17 and Figure 18 show that the actual value and predicted value differed by curricular subject area in their predictive power and linear fit for semester-long and year-long courses.

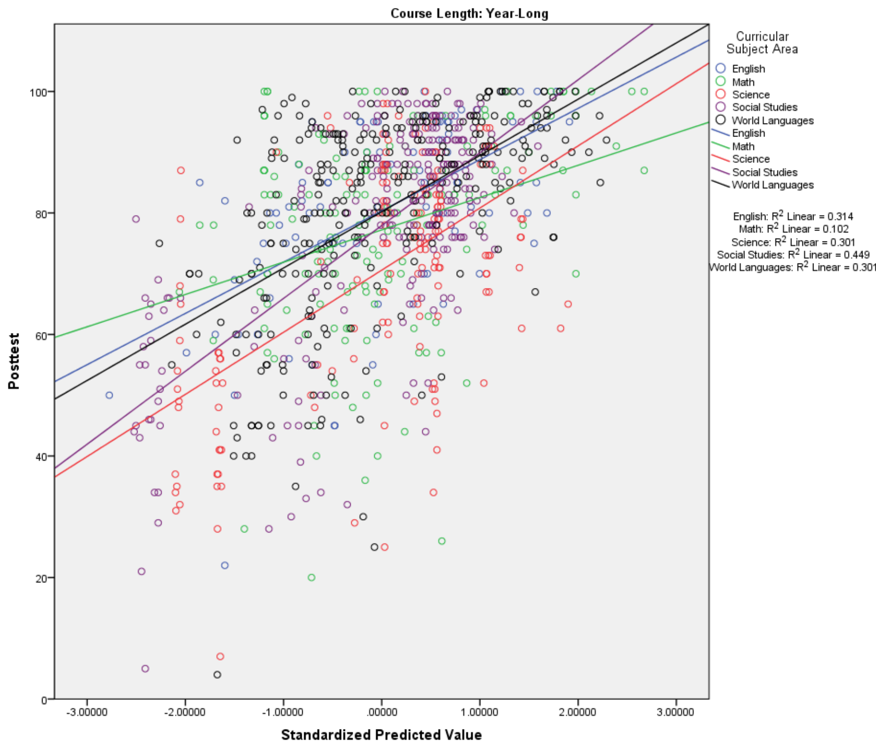

Figure 17. Scatterplot of posttest scores and standardized predicted values for year-long courses split by curricular subject area with a linear fit line.

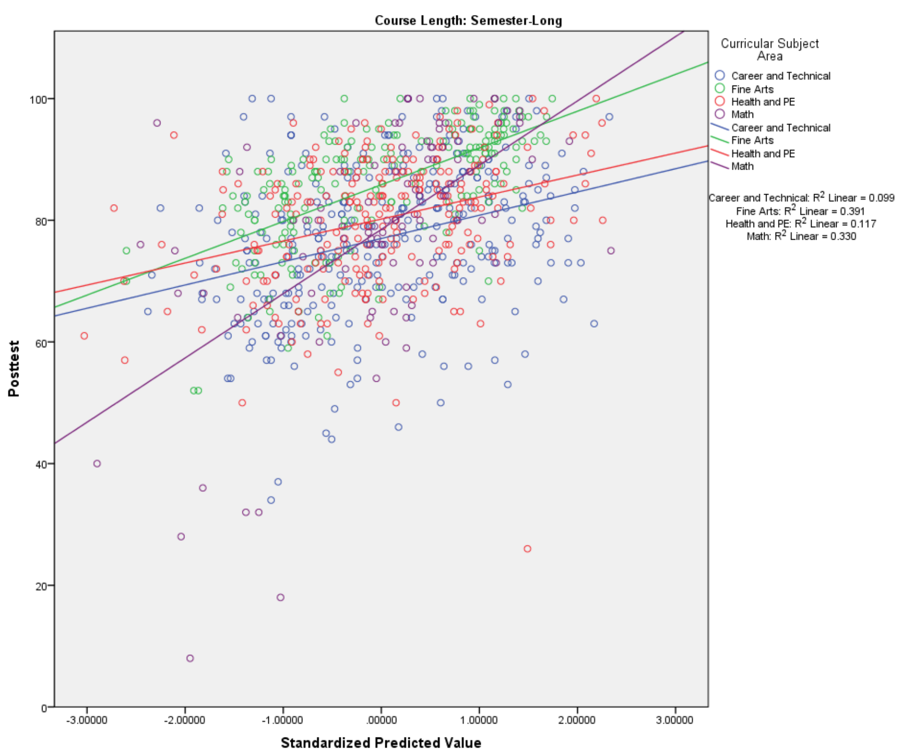

Figure 18. Scatterplot of posttest scores and standardized predicted values for semester-long courses split by curricular subject area with a linear fit line.

CHAPTER V

Conclusions and Recommendations

The purpose of this quantitative study was to evaluate student learning and achievement in online secondary courses through the frequency of LMS tools used by instructors as an objective measure. The LMS tools were pedagogically supported by Chickering and Gamson's Seven Principles for Good Practice. One of the characteristics of effective student learning was frequent interaction, and this study used the frequency of the LMS update, assignment, test, and discussion board tools. The objective of the study was to determine if the frequency of student interactions through the LMS tools had an effect on student learning and achievement. Specifically, the following research questions were explored:

RQ1. To what extent does the frequency of LMS update, assignment, test, and discussion board tools used by instructors predict semester final grade achievement by students in online secondary courses after controlling for prior learning?

RQ2. To what extent does the frequency of LMS update, assignment, test, and discussion board tools used by instructors predict posttest learning by students in online secondary courses after controlling for prior learning, and does the effect vary by course length?

RQ3. To what extent does curricular subject area in addition to the frequency of LMS tool use affect the prediction of student achievement and student learning in online secondary courses?

Summary of Procedures

The data for the study were received from the Research and Evaluation Branch of the organization in a de-identified Excel file. The procedure as identified in the proposed framework for data mining in e-learning included three main steps: logging the data, data pre-processing, and data mining (Kazanidis et al., 2009). The data logged in the Excel file contained the updates, assignments, tests, and discussion boards for each course. The student semester final grades, pretest scores, and posttest scores were included on a tab within the Excel file for each course. The data logged by the Research and Evaluation Branch contained all the information necessary to conduct the study but required data pre-processing to create a dataset for analysis in IBM SPSS Statistics 24. The data for LMS tool frequency contained 36,858 records that were identified by tool type. The data were pre-processed to create a list of unique courses by school year, with total counts for updates, assignments, tests, and discussion boards.

The initial student record data received for the analysis contained 7,117 student records. Student records that did not contain a pretest score were excluded from the analysis. This resulted in the exclusion of 4,700 records that were missing pretest scores. The remaining student records with pretest scores contained a corresponding posttest score. Regarding semester final grades, there were 704 incomplete records which had a pretest score but did not contain a semester final grade that were also excluded from the analysis. The remaining student data for analyses contained 2,188 posttest scores and 3,043 semester final grades. Each student record for a course had the frequency of updates, assignments, tests, and discussion boards added to the student record. The combined data resulted in a dataset that was imported into SPSS and analyzed.

The data mining was achieved through hierarchical multiple regression. The dependent variables were semester final grades and posttest scores. The independent variables were entered into the regression analysis in hierarchical blocks for analysis. The first block contained the pretest score variable. The second block contained the variables for frequency of the LMS tools of updates, assignments, tests, and discussion boards. The third block contained the curricular subject area dummy variables. There were two school years of student records, and the data were split by school year into SY1415 and SY1516 for analysis. Posttest scores existed as both semester-long and year-long values, which required an additional split of the data by course length.

The curricular subject area dummy variables entered into Model 3 were compared to math. Significant differences between curricular subject areas were found when compared to the math comparison group. The differences in curricular subject area were further analyzed by splitting the dataset by the curricular subject area nominal variable for both semester final grade and posttest score dependent variables. The analysis did not include the dummy variables in Model, 3 as the data were already split and grouped by curricular subject area. Finally, the effect on the predictive power of the LMS tools was compared.

Summary of Findings

The study used a hierarchical multiple regression which allowed pretest scores, a measure of prior learning, to be evaluated first. The four models for posttest scores and two models for semester final grades together averaged 6.6% prediction of the variance. When split by curricular subject area, pretest scores in fine arts and English had < 10% prediction of the variance for semester final grades and posttest scores. The results confirmed the need to use pretest as a measure of prior learning as a control variable in the regression analyses.

RQ1: The effect of LMS tools on semester final grades (achievement). The LMS update tool, assignment tool, test tool, discussion board tool were the primary focus for the study, and the results were evaluated by the change in R^2 from Model 1 to Model 2. The change in R^2 for LMS tools were statistically significant in both SY1415 and SY1516 for semester final grades. While the change in R^2 was significant, the effect size indicated that there was no effect. Only the LMS assignment tool was a significant contributor of predictive variance for semester final grades, but it was found to have no effect and was a negative (inverse) relationship. Therefore, LMS tools were not considered to have an effect for semester final grades when categorized by school year. In this study, semester final grades were a measure of student achievement which has subjective elements. To account for the subjective elements in semester final grades, the study also included objective posttest scores to evaluate student learning.

RQ2: The effect of LMS tools on posttest scores (learning). The change in R^2 for LMS tools for posttest scores was statistically significant for all four models and had small to medium effects. Posttest scores measured student learning for a single semester for the entire school year. Because the student learning measure spanned course lengths, the posttest scores for school year were further split by semester-long and year-long courses, resulting in four models for LMS tools. The LMS update tool was a significant predictor in all four models and had a small effect size. For semester-long courses, the LMS update tool was positively related to posttest scores but negatively related for year-long courses. The LMS discussion board tool was a significant predictor in two models, with a small effect size and positive relationship to posttest scores. The LMS assignment tool was a significant predictor for one model, with a small effect size and positive relationship to posttest scores. The LMS test tool was a significant predictor for one model, with a small effect size and negative relationship to posttest scores. Therefore, LMS tools were considered to have an effect on posttest scores. A negative relationship between the LMS test tool and posttest scores was identified and further evaluated during the analyses of curricular subject area. Even with the negative relationship of the LMS test tool, using all four LMS tools in the model improved the predictive power of the regression equation.

RQ3: The effect of curricular subject area and LMS tools on semester final grades and posttest scores. The effect of curricular subject area was first analyzed independently through univariate GLM ANOVAs for semester final grades and posttest scores. Levene's test for semester final grades and posttest scores indicated unequal variances and a rejection of the null hypothesis. The unequal variances for curricular subject area could explain the scatterplots for semester final grades and posttest scores, which showed slight heteroscedasticity when analyzed by school year. The curricular subject area between-subjects effect for semester final grades and for posttest scores was also significant ($p < .001$). The results indicated that curricular subject areas had significantly different predictive variances. The significant independent test results required further hierarchical regression analyses of semester final grades and posttest scores to determine the effect of curricular subject area on the predictive power of LMS tools.

While the LMS tools did not have a significant effect on semester final grades when split by school year, they did have a small effect when split by curricular subject area. Therefore, the summary of findings for curricular subject area included both semester final grades and posttest scores dependent variables. The LMS tools added 10% (career and technical education), 7% (fine arts), and 7% (world languages) predictive power for semester final grades after accounting for the pretest score variance. The LMS tools for career and technical education, fine arts, and world languages were statistically significant and had small effects. The LMS tools were not significant for English, health and PE, math, science, and social studies for semester final grades. It can therefore be concluded that LMS tools are not a strong predictor for student achievement as measured through semester final grades. Student achievement, as measured by semester final grades, includes subjective elements which can affect predictive power. These findings support this studies design decision to incorporate both a subjective measure, semester final grades, and an objective measure, posttest scores, to assess the predictive effect of the LMS tools.

The LMS tools were shown to have the highest predictive power and largest effect when predicting posttest scores that were categorized by curricular subject area and course length. The LMS tools added 5% to 39% predictive power for posttest scores after accounting for the pretest score variance. Career and technical education SL was a small effect, with 6% variance prediction. For medium effects, the variance prediction was 20% for English YL, 17% for fine arts YL, 15% for math SL, and 16% for world languages YL. Finally, for the large effects, LMS tools added 29% variance prediction for science YL and 39% variance prediction for social studies YL. Based on the results of the study, curricular subject area was found to have a significant positive effect on the variance prediction of LMS tools. These results indicate that, for online secondary courses, the differences between school years is not as impactful as the differences between curricular subject areas. The results also indicate that LMS tools predict more of the variance in student learning as measured through objective posttest scores than student achievement as measured through subjective semester final grades.

The regression results, when compared by curricular subject area, showed the relationships between the coefficients for the LMS tools. The frequency of the LMS test tool was higher than the LMS assignment tool only in the curricular subject areas of fine arts and math. As the frequency of assignments increased, the frequency of tests decreased in all subject areas other than fine arts and math. English, fine arts, science, career and technical education SL, English YL, science YL, and social studies YL had positive predictive coefficients for assignments but negative coefficients for tests. The LMS test tool had a negative relationship in all curricular subject areas apart from career and technical education, fine arts SL, and health and PE SL. While there were some inverse relationships, all four LMS tools contributed to the overall prediction of variance. The results of this study indicated that the inverse coefficient relationships among the curricular subject areas decreased the LMS tools' predictive variance when categorized by school year, but increased the predictive variance when categorized by curricular subject area. This was likely due to the inverse relationship of the LMS test tool for fine arts and math no longer being combined with the other curricular subject areas.

Findings Related to the Literature

The literature supported the concept that the level of interaction in a course affects student achievement (Bernard et al., 2009; Chickering & Gamson, 1987; Davidson-Shivers, 2009; Weiner, 2003). Student learning was also found to be most effective when the fundamental characteristics of active engagement, frequent interaction, and feedback were present (Harden & Laidlaw, 2013; Phillips, 2005; Roschelle et al., 2000; Sherman & Kurshan, 2005). The frequency of interaction can occur through learner-content, learner-instructor, and learner-learner (Moore, 1989). In an online environment, the interaction occurs through tools provided by the LMS, and the Seven Principles for Good Practice were found to be present in the online instructional tools (Dreon, 2013; Lai & Savage, 2013; Phillips, 2005; Ray, 2005; Woods, 2004). The results of this study support previous research. The results also provide contrary findings for the frequency of assessments and the effect of curricular subject area.

Frequency of interaction. The frequency of interaction can occur through learner-content, learner-instructor, and learner-learner (Moore, 1989). The LMS tools provided learner-content (tests), learner-instructor (updates, assignments), and learner-learner (discussion boards). The frequency of LMS tool use did not have a significant effect for predicting student achievement as measured through semester final grades however it did have a significant effect for predicting student learning as measured through posttest scores. The learner-instructor category that included updates and assignments contained four models that were positively related to posttest scores and had small effects. The learner-learner category that included discussion boards had two models that were positively related to posttest scores and had small effects. The learner-content category that included tests contained one model that was negatively related to posttest scores and had small effects.

The negatively associated LMS test tool contradicted the previous research that supported the idea that increased frequency of tests would result in an increase of student learning and achievement. This study involved online secondary school students who primarily interacted with tests that were auto-graded and did not require teacher feedback and interaction. The previous research for the frequency of assessments was conducted in a traditional face-to-face environment with mostly higher education students (Gocmen, 2003; Khalaf & Hanna, 1992; Martinez & Martinez, 1992). In online education, it was found that the relative magnitude of the interaction was a predictor of student achievement (Bernard et al., 2009; Hawkins, 2011; Lou et al., 2006). This study supports the idea that the relative magnitude of the interaction through LMS tools can predict student achievement and learning.

LMS update tool. The study by Lonn (2009) defined a basic interaction as any kind of communication that takes place online within an LMS tool, such as an update. Updates were found to be a great strength of the LMS and the main source of learner-instructor interaction (Graham et al., 2001). The frequency of updates in the LMS was found to be a significant predictor of posttest scores but was a small effect. Semester-long courses were positively related to posttest scores but year-long courses were negatively related. The LMS update tool was the most frequently used LMS tool in English and fine arts but was not a significant predictor. The results of this study showed that updates were not the main source of learner-instructor interaction and the effects were small and conflicting and would benefit from further study.

LMS assignment tool. The instructor provides practice and feedback through the LMS assignment tool. The quantity or frequency of interactive events is supported by Kuh's (2003b) statement that "the more students practice and get feedback on their writing, analyzing, and problem solving, the more adept they become" (p. 25). The LMS assignment tool had the highest mean frequency across curricular subject areas for the LMS tools. This supports the findings of Pyke's (2007) study that assignments were the most frequently used form of feedback in online courses. The LMS assignment tool was found to have a small and significant positive effect on posttest scores for SY1516. For semester final grades, the LMS tools did not have a significant effect when separated by school year but the LMS assignment tool was significant when split by curricular subject area for career and technical education, math, social studies, and world languages.

LMS test tool. The LMS test tool has the option of providing automatic feedback for correct and incorrect answers, but the data mined in this study did not contain information about individual test questions. Therefore, it cannot be assessed whether automatic feedback supports the studies by Lai and Savage (2013) or Ibabe and Jauregizar (2010). The LMS test tool was not a significant predictor for semester final grades and was significant for only one of the four models for posttests scores. The significant posttest score predictor for SY1415 SL was negatively related, as the frequency of tests increased, posttest scores were found to decrease. Tests were also significant but negatively related for the curricular subject areas of fine arts, science, and world languages. The LMS test tool is similar to providing a multiple-choice test in a traditional classroom. However, the results of this study do not support the meta-analysis study by Gocmen (2003) that frequent testing in a traditional classroom was beneficial to student learning and academic achievement. This is surprising, as previous research did not find significant differences in student learning and achievement when comparing online and traditional classes (Lim et al., 2008; Parker, 2015; Schmidt, 2012, U.S. Department of Education, 2010). It was outside the scope of this study to assess the other advantages of frequent testing cited by Gholami and Moghaddam (2013). It must be noted that this study utilized tests in a fully online secondary school environment and that, in terms of research K-12 has had few rigorous research studies related to the effectiveness of online learning (U.S. Department of Education, 2010). Additional research would be needed to determine if the population, environment, or test design resulted in the negative relationship to posttest scores.

LMS discussion board tool. The frequency of the LMS discussion board tool was least used in all subject areas. The English curricular subject area used discussion boards the most. The LMS discussion board tool was the only student-student interaction evaluated. The frequency of discussion boards had a small but positive effect on posttest scores. The curricular subject areas of math and world languages had statistically significant positive effects for semester final grades and posttest scores, but the other subject areas were not significant or negatively related to the dependent variable. Previous research related to the frequency of posts within discussion boards or the quality of the interaction contained in the posts was outside the scope of this study.

Curricular subject area. This study did not have the same findings as the meta-analysis by Gocmen (2003) that stated that effect sizes for curricular subject area were not found to be significant. The study by Gocmen (2003) only evaluated the frequency of tests in a traditional classroom. This study had the highest frequency of cases in the social studies curricular subject area, and a majority of the studies analyzed by Gocmen (2003) were also in social sciences. This study evaluated eight subject areas with similar course design, while previous research evaluated only one specific course at one specific higher education institution (Bowman et al., 2014; Macfadyen & Dawson, 2010; Weinberg, 2007; Wong, 2016). The results of this study determined that curricular subject area predicted 3% of the variance for student achievement (semester final grades) and 6% of the variance for student learning (posttest scores). It can be inferred through these results that curricular subject area is an important factor for analysis and that not accounting for curricular subject area may lead to inaccurate results. The significant unequal variance among curricular subject areas when evaluating student learning and achievement in online secondary schools demonstrates that results should not be generalized across curricular subject areas. Specifically, this study demonstrated that the LMS tools of updates, assignments, tests, and discussion boards varied in the significance and effect across the eight subject areas. The coefficients level of predictive variance was significantly different across curricular subject areas and therefore this study reports the LMS tools as a combined model rather than evaluating the individual tools. The combined LMS tools had greater predictive power together when categorized by curricular subject area when assessing the effect on student learning and achievement.

Limitations

The data for this study were limited to the de-identified data provided by the Research and Evaluation Branch at the organization. The de-identified data did not allow the researcher to determine if the same student was enrolled in one course or more than one. The de-identified data also limited the ability to analyze the effect of the instructor on the course and did not indicate if the instructor had changed from school year 2014-2015 to school year 2015-2016. The study was delimited by the researcher to student records that contained pretest scores. The data provided were missing over 50% of pretest scores, either because the course did not contain a pretest or because students did not complete the pretest. The LMS used by the organization was also limited in the LMS tool details that could be extracted through the data mining process. The semester final grade as a measure of achievement had limitations due to instructor subjectivity and, as noted previously, the potential for instructor bias could not be analyzed with de-identified data. Instructor subjectivity in semester final grades may have affected the analysis but could not be accounted for. Because of the instructor subjectivity limitation, the study was designed to also analyze objective posttest scores.

Recommendations and Future Research

This study was focused on the effect of LMS tools on student achievement and student learning. The researcher also sought to determine if curricular subject area had an effect on the predictive power of the LMS tools. The semester final grades and posttest scores differed significantly by curricular subject. It is recommended, when analyzing online courses that belong to more than one curricular subject area, that the methodology contain a variable that allows curricular subject area to be split and compared. For the study of online asynchronous courses, it is recommended that results not be generalized beyond the curricular subject area that is being studied and that the specific curricular subject area be identified.

One of the main findings is that the predictive power of the LMS tools was increased when the curricular subject areas were analyzed individually instead of combined by school year. The range in variance predicted by the LMS tools when split by curricular subject area requires additional research. The largest effects were from year-long science and social studies courses, which previous research identified as the most frequently researched curricular subject areas. With the wide variance between curricular subject areas, it is recommended that additional research include curricular subject areas that do not fall within the categories of science and social studies. The studied population was primarily twelfth-grade students, which may have influenced which courses online students selected.

One of the main benefits of this study was that the online courses were from the same curriculum provider, which provided a consistent course design across all curricular subject areas. It is recommended that future studies that compare curricular subject areas consider the effect of course design on the independent variables. For example, one curriculum provider may design its courses with more collaboration activities, which, in the case of this study, would increase the number of discussion boards. This study researched online courses in which a majority of the content and graded activities were provided to the instructor, thus allowing the LMS tool use for each course to be more consistent throughout the two school years studied. If the course content is generated exclusively by instructors, future studies should also consider the influence of the instructor on the use of the LMS tools. In terms of instructor influence, the LMS update tool was ungraded and the frequency of use was entirely dependent on the instructor of the course. The results indicated that, while the LMS update tool was most frequently used in

English and fine arts, it was not significant, and other curricular subject areas were small effects with positive and negative relationships to posttest scores. Based on the results of this study future research studies using the LMS update tool should include the instructor and an identifier of the content type of the update (reminder, informative, feedback, etc.). This study was not able to identify if specific instructors had preferences for the frequency of updates posted, since instructor information was not included in the de-identified dataset.

This study found that pretest scores as a measure of prior learning were consistently significant predictors across all three research questions. The literature supported the idea that pretest scores can measure prior learning. This study accounted for prior learning using pretest scores in a hierarchical multiple regression. While the requirement for pretest scores did exclude over half of the student record data received, there was still a large sample that remained for analysis. The use of pretest and posttest assessments in this study allowed for an objective measure of student learning. It is recommended that future research studies evaluating student learning verify that the course content includes a pretest and posttest measure. For this study, the researcher was hopeful that instructors used a pretest and posttest in the course, but it was not required, only recommended. Based on the number of student records that did not contain pretest and posttest scores, the researcher recommends that the organization continue providing pretest and posttest assessments to students and reinforce to instructors the value of assessing the students' prior knowledge. Pretest scores were a significant predictor and improved the overall prediction of the variance in the full model that included LMS tools. For future research in online secondary schools, it is recommended that pretest scores be included in prediction analyses to account for prior learning.

This study successfully utilized the educational data mining framework proposed by Kazanidis et al. (2009) for e-learning that included logging the data, data preprocessing, and data mining. For the logging data step, it is recommended that the researcher have a technical understanding of the LMS application and database structure or have an information technology consultant/partner who is able to collect and extract the data from the LMS. For the data pre-processing step, it is recommended that the researcher have an understanding or detailed documentation that includes the names and descriptions of the data fields. It is also recommended that the researcher request translation tables for numeric values to label names. In this study, the grading periods were strings of numbers that related to labels for each grading period, and translation tables were necessary for pre-processing. For the data mining step, it is recommended that, with a large dataset, that categorization using variables identified in pre-processing be used to control for variance in populations. If the proposed sample size is large for the data mining analysis, it is recommended that effect sizes also be calculated, as a variable could be statistically significant but have no real effect.

It is important to note that this study was correlational in nature and did not evaluate causation. Therefore, changes to educational policies based on the results of this study are not recommended. In online secondary schools, it is recommended that administrators and instructors consider the differences in curricular subject areas when evaluating semester final grades (achievement) and posttest scores (learning). Additional research, including experimental design, is needed to confirm that increasing the frequency of use for the various LMS tools results in increased semester final grades and posttest scores. The LMS tools' prediction of the variance in semester final grades and posttest scores was only a portion of the overall variance. Future studies should determine if there are other variables that should be included for analysis.

Conclusion

The theoretical framework for this study utilized Chickering and Gamson's Seven Principles for Good Practice to determine which LMS tools should be included for analysis. The LMS tools of updates, assignments, tests, and discussion boards are pedagogically supported by SPGP principles 1, 2, 3, and 4. Principle 1 encourages contact between students and faculty, Principle 2 develops reciprocity and cooperation among students, Principle 3 uses active learning techniques, and Principle 4 gives prompt feedback (Chickering & Gamson, 1987). Interaction is often viewed as necessary for student learning to occur in an online learning environment, and achievement outcomes favored more interaction over less interaction (Bernard et al., 2009; Davidson-Shivers, 2009; Weiner, 2003). Student learning was found to be most effective when the fundamental characteristics of active engagement/learning, frequent interaction, and feedback were present (Van Amburgh et al., 2007; Harden & Laidlaw, 2013; Phillips, 2005; Roschelle et al., 2000; Sherman & Kurshan, 2005). In the online secondary courses evaluated, the LMS assignment tool on average was the most frequency used. The LMS assignment tool encourages interaction between students and faculty. The LMS assignment tool also supports active learning through the concept of learning by doing (Chickering & Ehrmann, 1996; Dreon, 2013). The LMS assignment tool also requires an instructor to provide feedback. The minimal feedback would include points received out of points possible but can also include more detailed feedback through rubrics, written feedback, attached documents, and recorded audio/video from the instructor. Based on literature support, the LMS assignment tool was anticipated to be a significant predictor of student learning. To evaluate student achievement, semester final grades were analyzed as a dependent variable. To account for the inherent subjectivity in semester final grades, posttest scores were also analyzed as an objective dependent variable. Both dependent variables were measured using the same independent variables.

This study employed a data mining procedure to determine if LMS tools could predict semester final grades (achievement) and posttest scores (learning). The findings suggest that the LMS tools can predict posttest scores but not semester final grades. Additionally, the study determined whether curricular subject area had an effect on the predictive power of the LMS tools. The findings of this study suggest that curricular subject area can predict the variance in semester final grades and posttest scores. The findings also suggest that there was unequal variance across curricular subject areas for the dependent variables. By categorizing the courses by curricular subject area, the predictive power of the LMS tools was positively affected. The LMS tools had large effect sizes in science and social studies for posttest scores when categorized by curricular subject area.

Additionally, the LMS update, assignment, test, and discussion board tools varied in predictive strength and relationship to the dependent variables. The findings of this study indicated that the LMS assignment and discussion board tools were significant predictors, with small positive effects for posttest scores. The findings also suggested that the LMS test tool was a significant predictor, with a small negative relationship to posttest scores. The negative relationship found in this study contradicts the literature related to the frequency of tests in traditional classroom environments. The LMS test tool was primarily a learner-content interaction, whereas assignments primarily were a learner-instructor interaction and discussion boards were primarily a learner-learner interaction. The LMS update tool was a significant predictor for posttest scores but had a small positive relationship for semester-long courses and a negative relationship for year-long courses. The frequency of the LMS tools varied by curricular subject area. Specifically, the LMS assignment tool had the highest mean frequency across all subject areas.

The curricular subject area math had the highest frequency of the LMS test tool, and the LMS test tool was also found to be negatively correlated with the LMS assignment tool. The negative correlation of assignments and tests in math shows that, as the number of tests increase, the number of assignments decrease. For studies evaluating frequency of assessments, this study found that the math curricular subject area used the LMS test tool most frequently, while reducing other LMS tool use. Based on this study, it can be concluded that the math curricular subject area most significantly used the LMS test tool over the LMS assignment tool. The LMS test tool had a negative effect on semester final grades and posttest scores for math. The researcher is not suggesting that math courses should convert all tests to assignments. Math was used as the comparison curricular subject area for the dummy variables, and the other subject areas showed significant differences. This study highlights the difference between math and the other curricular subject areas. It is recommended that research studies in the online secondary school environment account for the difference in math when generalizing results related to LMS tool use. While the significance and effect size varied across subject areas, including all four tools in the regression equation resulted in the highest percentage of variance predicted.

In conclusion, the results of this study have been presented in context with the literature related to the SPGP, frequency of interaction, feedback, and instructional tools. The literature supported that pretests as a measure of prior learning are a good predictor for learning and achievement. This study used pretest scores as a control variable in a hierarchical multiple regression, and pretest scores were found to be significant predictors for semester final grades and posttest scores. The LMS tools, when added to pretest scores, contribute an additional 3%

(SY1516 YL), 4% (SY1415 SL), and 8% (SY1516 YL) prediction of the variance of posttest scores, with a small effect. The LMS tools for SY1415 YL predicted 14% of the variance, with a medium effect. Specifically, the findings supported the linear positive relationship between assignments and discussion boards for posttest scores. The findings did not support the idea that the LMS tools were a significant predictor for semester final grades when categorized by school year. By categorizing the courses by curricular subject area, the LMS tools were significant predictors for semester final grades and posttest scores. The LMS tools categorized by curricular subject area had small effects for semester final grades. The largest overall effect of the LMS tools was on posttest scores categorized by curricular subject area. Career and technical education SL was a small effect, with 6% variance prediction. For medium effects, the variance prediction was 20% for English YL, 17% for fine arts YL, 15% for math SL, and 16% for world languages YL. Finally, for large effects, LMS tools added 29% variance prediction for science YL and 39% variance prediction for social studies YL. Therefore, curricular subject area does have an effect on the predictive power of LMS tools. This study provides a further example of educational data mining and the results that can be achieved with a strong pedagogical framework. Future researchers and practitioners should carefully develop a data mining procedure that is pedagogically supported and should account for variation among curricular subject areas when analyzing courses from more than one curricular subject area.

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