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An Evaluation of an Adaptive Learning Tool in an Introductory Business Course

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by

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Dr. Sherry DeVore, Committee Member — March 17, 2016 — Date

Dr. Jeff Fulks, Committee Member — March 17, 2016 — Date

Dr. Terry Reid, Committee Member — March 17, 2016 — Date

Declaration of Originality

I do hereby declare and attest to the fact that this is an original study based solely upon my own scholarly work at Lindenwood University and that I have not submitted it for any other college or university course or degree.

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Abstract

Adding technology to the classroom has been an instructional strategy used by many higher-education institutions to increase student success, but merely adding computers, multimedia devices, and other technology to the classroom with pedagogical arbitrariness has proven to have little effect. The purpose of this study was to determine if using the adaptive learning technology (ALT) tool, LearnSmart, in seated introductory business courses would result in a statistically significant difference in unit exam scores, to analyze changes in exam performance through different time increments used of the ALT, and to investigate correlations between the student's metacognition in the ALT module and his or her performance on the unit exam. The population of this study consisted of students in nine sections of introductory business courses at three large community colleges in the Midwest. The first group of students did not use LearnSmart before the exam, the second group of students completed a 20-minute LearnSmart module for each chapter before the exam, and the third group of students completed a 40-minute LearnSmart module for each chapter before the exam. From the data collected and analyzed in this study, there was a statistically significant positive difference in exam scores of students in an introductory business course who completed the 40-minute LearnSmart modules prior to the exam compared to students who did not use LearnSmart. There was also a statistically significant correlation between a student's metacognitive score and his or her exam score.

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Chapter One: Introduction

The invention of adaptive learning, sometimes referred to as personalized learning or computer-assisted learning (CAL), stems from advancements in technology and also from the need for teachers to better understand the learning habits of students in increasingly larger classrooms (Fletcher, 2013). As more students are added to the classrooms of K-12 and higher education, teachers become less aware of how each individual student is learning and progressing (Johnson, 2011). Software engineers of adaptive technology are helping to change the situation, and proponents of adaptive learning have stated, "technology has finally made it possible to deliver individualized instruction to every student at an affordable cost" (Fletcher, 2013, p. 64).

Students, on average, perform two standard deviations better under one-on-one tutoring compared to standardized group instruction (Bloom, 1984). Bloom (1984) described this effect of personalized instruction as the *2 sigma problem* (p. 4). Until recently, the ability for a teacher to provide personalized learning and adaptability to each student has been difficult to achieve (Bain & Weston, 2012; Bloom, 1984). Adding technology to the classroom is one way Bloom (1984) suggested to help increase student success, but merely adding computers and other technology to the classroom with pedagogical arbitrariness has proven to have little effect (Bain & Weston, 2012). Relatively low-cost, personalized, adaptive learning technologies are needed along with a successful pedagogy to make them accessible to the masses, as opposed to only wealthy individuals who can afford expensive personalized educational tools (Tomlinson, 2014).

Adaptive learning technology (ALT) is the name given to a "computerized-learning interface that constantly assesses a student's thinking habits and automatically customizes material for him or her" (Fletcher, 2013, p. 66). Additional advancements in software and computer capabilities have made it possible to use computers as interactive teaching devices, and journals such as the *International Journal of Artificial Intelligence in Education* and *The Journal of Computer Assisted Learning* contain a plethora of articles that affirm this new approach (Griff & Matter, 2013). It is a relatively new technology and way of learning compared to the long-standing traditional system of physical teachers teaching students that dates back thousands of years (Brookfield & Preskill, 2012).

In a learning environment where a teacher is only directly responsible for one student, the teacher would be able to devote his or her attention to the student and would be able to understand how to tailor the curriculum to meet the needs of the student (Brookfield & Preskill, 2012). As more students are assigned to the teacher, he or she is forced to divide his or her attention between multiple students, thus essentially limiting the amount of information that can be known about each of the students (Bloom, 1984). Adaptive learning technologies have been created to bring back the one-on-one learning environment (Horn, 2012). The design of this study was created to focus on the use of the ALT, LearnSmart, in an introductory business course to see if it would impact assessment scores on a unit exam.

The background issues of the study are addressed in this chapter. Next, the theoretical framework and research about learning theories from which the study stems are presented. The underlying problem and purpose of the study, research questions and hypotheses, and key terms used in the study are addressed at the end of the chapter.

Background of the Study

Learning has been broadly defined as the process of internalizing the representational and communicative means of the subject matter (Engestrom, 2014). The learning theories that underpin traditional learning include cognitive development, knowledge construction, and knowledge representation (Engestrom, 2014; James, 2012; Piaget, 1972; Ultanir, 2012). Additional research on how e-learning theory could be different than those of traditional learning theories has been emerging (Haythornthwaite & Andrews, 2011), and that is why a focused study of an ALT in an introductory business course will further this research. Learning achievements by students using CAL programs have been made in the areas of mathematics and accounting (Phillips & Johnson, 2011), and CAL has been effective in the teaching of foreign languages (Lee et al., 2011).

Adaptive learning technology encompasses all three underpinning elements of constructivism: cognitive development, knowledge construction, and knowledge representation (Akbulut & Cardak, 2012; Gallagher, 2014; Johnson, 2011; Lee et al., 2011). Since the ALT is personalized to each student, the platform in which each person begins to learn is equal, unlike the traditional, seated classroom environment (Johnson, 2011). Each student brings with him or her a different base knowledge that was acquired in different ways, and each student will ultimately experience new information, known as assimilation, thus leading the student to make an attempt at accommodation (Piaget, 1972). Because the ALT uses algorithms to predict knowledge, students begin to travel different paths that bring them to the same end goal (McGraw-Hill Education, 2015). Through practice and repetition, it is expected that accommodation follows (Andrews, 2011).

Since the ALT is delivered by a computer, the adaptation of different learning styles can be achieved (Akbulut & Cardak, 2012). Learning styles may be accommodated in different ways through the use of the ALT. A student has options to see, hear, and manipulate text, animation, and audio recordings. There are also kinesthetic activities of clicking, dragging, and other manipulations of various parts of the environment for the student (Akbulut & Cardak, 2012; Fletcher, 2013; Waters, 2014; Webley, 2013). Students may be in a classroom or at home, in hotter or colder environments, or in bright or dimly-lit environments (James, 2012). The ALT is delivered in a mobile platform, thus traditional limitations of the classroom fall away (James, 2012). The culmination of these cognitive-development theories and factors associated with CAL creates a structure for re-imagining learning from a multi-modal vantage point to explore what substantial difference using technology in the educational process can make for learning (Haythornwaite & Andrews, 2011).

The ideas of adaptive learning, and what would eventually include ALTs, have been around for centuries as teachers and researchers envisioned ways of trying to craft learning to fit each student in the classroom (Brookfield & Preskill, 2012). Though costs and technology limitations halted advancements, doors have been opened to the use of technology in the last two decades, and many K-12 and higher education institutions have been adding technology-assisted learning tools at a rapid pace (Hopkins, 2014). The addition of technology in education has become commonplace, but there are few increases in academic success at which to point to validate the effectiveness of these additions (Bain & Weston, 2012). Indeed, some researchers have argued that most of these technologies burden the teacher greatly and have little to offer in the way of active learning for the student (Akbulut & Cardak, 2012). Technologies that use personal, adaptive learning could shift the role of the teacher to that of a moderator or interpreter of learning, thus engaging the student directly with the material (Freeman et al., 2014; Jensen, Kummer, & Godoy, 2015).

Theoretical Framework

Adaptive learning is underpinned by the theories of constructivism, active learning, and metacognition (Gallagher, 2014). Constructivist learning is a learning theory that states all knowledge is constructed from previous knowledge, regardless of how one acquires the information (Engestrom, 2014; Piaget, 1972). Constructivist learning involves honing and refining current beliefs about something through new experiences and information (Piaget, 1972).

The theory of cognitive development was created by psychologist Jean Piaget (1972) in the mid-twentieth century and applies to the cognitive development process of infants, children, and adults. Piaget (1972) found that humans learn from activities that require trial and error, and finding error in preconceived ideas leads towards an accurate understanding of the material. Piaget’s (1972) work branches into the two distinct parts of assimilation and accommodation (Isaacs, 2015; Müller, Ten Eycke, & Baker, 2015). Assimilation is the process of a learner adapting to new ideas or new concepts that were previously unknown (Isaacs, 2015; Müller et al., 2015). When a person is presented with information he or she did not previously know, then that person must begin to determine how this new information correlates to his or her preconceived idea (Illeris, 2015). The assimilation process that takes place represents the initial form of learning (Piaget, 1972). Piaget (1972) determined learning was not complete until the learner successfully adapted his or her beliefs to accommodate the new piece of information. Whether the learner is an infant or an adult, the new constructs that are presented must be accepted as replacements of his or her former beliefs (Illeris, 2015; Piaget, 1972). Once the person accepts this new construct has changed his or her understanding of reality, then accommodation usually occurs in order to make the new information part of his or her schema (Piaget, 1972).

In the attempt to educate children or adults, providing isolated lectures often does not improve learning (Jensen et al., 2015; Lord, Prince, Stefanou, Stolk, & Chen, 2012). It should be noted learning can be achieved through a lecture format, but these instances usually occur after people have first negotiated with the subject matter on their own (Schwartz & Goldstone, 2015). In order to use cognitive structuring, teachers must constantly be guiding the student into new knowledge to build on previous knowledge (Schwartz & Goldstone, 2015). It is evident through research that learning increases when attention is paid to the "knowledge and beliefs that learners bring to a learning task, and instructors use this knowledge as a starting point for new instruction and monitor students' changing conceptions as instruction proceeds" (Stanaityte, 2013, p. 21).

The ALT uses algorithms to predict knowledge; therefore, students are able to have a personalized learning experience that ultimately guides them through a constructivist pedagogy in order to learn the material (New England Journal of Medicine [NEJM], 2014). The ALT assumes the role of the instructor in presenting new constructs to students (McGraw-Hill Education, 2015; NEJM, 2014; Waters, 2014; Webley, 2013). The ALT requires practice and repetition to learn the information, thus accommodation should occur (NEJM, 2014; Piaget, 1972). The ALT is delivered to the student by computer; therefore, the incorporation of different learning styles can be achieved (Akbulut & Cardak, 2012; Fletcher, 2013; Haythornthwaite & Andrews, 2011; Reich, 2014; Waters, 2014; Webley, 2013; Zimmer, 2014). Students are presented information in a variety of ways, including variations of text styles, visual displays, animation, audio recordings of sounds, kinesthetic activities of clicking, dragging, and movement of objects, manipulation of various parts of the information, and the manipulation of the environment of the student (Akbulut & Cardak, 2012; Fletcher, 2013; Waters, 2014; Webley, 2013).

Active learning is anything that involves students participating in activities outside the realm of simply listening and thinking about the information they are trying to learn (Freeman et al., 2014). Active learning is also defined as anything in a course that all students in a class are asked to do other than the mere act of watching the instruction, listening to the instructor, or note taking (Lord et al., 2012). This field of active learning is a hands-on approach to learning that involves the student actively engaging with the information (Freeman et al., 2014; Jensen et al., 2015). Active learning is not as rigid as kinesthetic learning, in which one actually accomplishes a physical task, but approaches this standard by moving the student one step closer to gaining knowledge by a means other than simply hearing it or watching it (Lord et al., 2012).

Active learning draws a student one step closer to understanding what he or she knows and does not know, since there is a level of interaction and engagement with the information (Freeman et al., 2014; Lord et al., 2012). New developments in the science of learning also are bringing to light the importance of people taking control and ownership of their own learning (Chew, 2014). Since understanding is viewed as critically important, students must be able to know when they understand something and when they need more information to help them understand (Chew, 2014).

Metacognition is the actual attention paid to monitoring and directing one's own thinking (Chew, 2014). Metacognition refers to peoples' abilities to predict their performances on various tasks based on confidence levels and other internal inputs in order to adjust the amount of information needed from an instructor in the future (Chew, 2014). Students gain understanding from metacognition, because metacognition allows them to develop their own assessment of knowledge, assess what they do and do not know, and then make future decisions based on this knowledge (Chew, 2014; Kilgo et al., 2014). If a student is asked to take a test over a particular subject, then he or she has a predetermined level of confidence in the knowledge he or she has prior to taking the test (Butler & Winne, 1995; Chew, 2014; Kilgo et al., 2014). If the student feels unprepared for the test, then additional studying will probably be the remedy (Chew, 2014). Once the test is complete, the student then analyzes the results to find out if more study is needed in particular areas (Chew, 2014).

Students have certain metacognitive skills, but additional metacognitive instruction is needed to inform the student where he or she should focus in order to achieve academic improvement (Tanner, 2012). This constant assessment and feedback feature is key to properly using metacognition (Chew, 2014), but data from research studies indicate most students lack the ability to understand their own knowledge level

(Kilgo et al., 2014). Metacognition is crucial to active learning, but many students fail to understand how to use it (Kilgo et al., 2014).

Adaptive learning technology utilizes the theory of constructivism and creates an opportunity for students to be presented with new information that challenges their current beliefs, which provides assimilation and a chance at accommodation (NEJM, 2014; Piaget, 1972; Waters, 2014; Webley, 2013). Students then must actively engage and interact with the material and receive feedback, which draws directly on the theory of active learning (Bertsch & Pesta, 2014; Lord et al., 2012; NEJM, 2014; Waters, 2014; Webley, 2013). Lastly, ALTs build upon the theory of metacognition through the collection and use of metacognition data to determine future courses of study for the student (McGraw-Hill Education, 2015; NEJM, 2014; Waters, 2014; Webley, 2013).

Statement of the Problem

A review of current literature has revealed a lack of empirical studies of ALTs being used in business courses. Many of the studies and findings that exist are not empirical in nature, and the results of the studies are often either self-reported by the teacher or anecdotal with no additional information existing relating to the reliability or validity of the study (McGraw-Hill, 2015). Cooke et al. (2008) systematically reviewed 201 internet-based instruction studies in the health discipline. The majority of these studies revealed a positive effect of using CAL platforms (Cooke et al., 2008). A few studies have been conducted in the fields of mathematics and accounting and resulted in significantly faster transaction analysis performance when students were required to use an ALT (Phillips & Johnson, 2011). Students also were able to significantly increase foreign language speaking skills when using an adaptive learning intelligent tutoring system (Lee et al., 2011). With increasing amounts of money being used to purchase ALTs (Hopkins, 2014), and approximately 40% of K-12 institutions that responded to a 2013 *Project Tomorrow* educational survey (Jensen et al., 2014) stating the desire to implement a non-lecture-based style of instruction in upcoming years, it is worthwhile to assess the effects of ALTs on student learning.

Purpose of the Study

The purpose of this study was to determine if using the ALT, LearnSmart, in seated introductory business courses would result in a statistically significant difference in unit exam scores. The researcher also sought to examine changes in exam performance when different time increments were used of the ALT. Furthermore, the researcher also probed the general implications of metacognition of the student's confidence in the ALT module and his or her performance on the unit exam. The findings of this study could be used by higher-education institutions to inform decision makers whether or not to use an ALT in introductory business courses. The findings of this study could be used by instructors of business courses in creating instructional strategies in the future that could increase student learning through the addition of an ALT. Additionally, the findings could be used by the developers of the ALTs in future innovation of the technologies.

Research questions and hypotheses. The following research questions guided the study:

1. Is there a statistically significant difference in mean exam scores based on the amount of time the ALT, LearnSmart, is used in an introductory business course?

H1_0: There is no statistically significant difference between mean exam scores based on the amount of time the ALT, LearnSmart, is used in an introductory business course.

H1_a: There is a statistically significant difference between mean exam scores based on the amount of time the ALT, LearnSmart, is used in an introductory business course.

2. Is there a statistically significant correlation between a student's metacognitive confidence in answering questions in LearnSmart modules and his or her unit exam score?

H2_0: There is no statistically significant correlation in the unit exam scores in an introductory business course of students based on metacognitive confidence in answering questions in LearnSmart modules.

H2_a: There is a statistically significant correlation in the unit exam scores in an introductory business course of students based on metacognitive confidence in answering questions in LearnSmart modules.

3. Is there a statistically significant difference in mean exam scores based on having prior experience using LearnSmart?

H3_0: There is no statistically significant difference in mean exam scores based on having prior experience using LearnSmart.

H3_a: There is a statistically significant difference in mean exam scores based on having prior experience using LearnSmart.

Definition of Key Terms

For the purposes of this study, the following terms are defined:

Adaptive learning technology. Adaptive learning technology is the name given to a "computerized-learning interface that constantly assesses a student's thinking habits and automatically customizes material for him or her" (Fletcher, 2013, p. 66). The invention of adaptive learning, also known as personalized learning, stems from advancements in technology, but it also comes from the need for teachers to better understand the learning habits of students in larger classrooms (Fletcher, 2013). Adaptive learning technology uses algorithms to create a personalized learning path for each student, thus addressing his or her individual needs and goals (Klasnja-Milicevic, Vesin, Ivanovic, & Budimac, 2011).

Algorithm. Algorithms are broadly defined as step-by-step procedures for solving a problem or accomplishing some end (Dietvorst, Simmons, & Massey, 2014). Algorithms contain a series of contingencies that have specific actions (Hickman, 2013).

E-learning. E-learning is a compound, hybrid term that encompasses traditional offline-learning and online learning via electronic means (Andrews, 2011). It is a "re-conceptualization of learning that makes use of not only instructor-led pedagogy but all the flexibility that asynchronous, multi-party contribution can bring" (Andrews & Haythornthwaite, 2007, p. 19).

LearnSmart. LearnSmart is an online study tool developed by Area 9 Learning (McGraw-Hill, 2015). LearnSmart individually diagnoses a student's knowledge of a subject area based on an algorithm-based series of subject matter questions coupled with metacognitive indicators (McGraw-Hill Education, 2015). Based on the performance of the student's responses, LearnSmart assesses what each student has mastered, what he or she needs to study further, and how much time he or she needs to study the material (McGraw-Hill Education, 2015). LearnSmart probes the student on learning objectives until the algorithm indicates the student is confident and consciously competent in his or her understanding of the subject matter (NEJM, 2014).

Metacognition. Metacognition is the ability for one to know what one knows and what one does not know (Chew, 2014). It is one's ability to predict his or her performances on various tasks based on confidence levels and other internal inputs in order to adjust the amount of information needed in the future (Tanner, 2012).

Limitations and Assumptions

The following limitations were identified in this study:

Population and sample demographics. This study encompassed three large community colleges in the Midwest. The relatively small sample size, limited geographic location, and narrow demographic of the population might have introduced bias into the study (Bluman, 2014; Navidi & Monk, 2014). A sample is said to be biased if the "results from the sample of a population are radically different from the results of a census of the population" (Bluman, 2014, p. 3).

Instrument. The unit exam consisted of 30 multiple-choice and true-false questions and was relatively limited compared to the large number of questions that could be asked to measure learning. Furthermore, multiple-choice and true-false questions are only two types of questions that could potentially be used to assess learning (Dennehy, 2014). The use of other forms of assessment could capture student learning in ways multiple-choice and true-false questions do not (Dennehy, 2014).

Pedagogy. This term is used to describe the act of teaching and the methods teachers use in order to increase learning (Pretorius, 2014). In order for teachers to teach successfully, a series of planned actions that will lead to greater understanding must be applied (Pretorius, 2014). Since this study involved multiple classes, there was no way to guarantee each class of students received the same information from the teachers or that the pedagogy was successful.

In addition to the differences in pedagogies among the instructors, an additional limitation occurs. The *Hawthorne Effect* states individuals behave differently when they know they are being watched (McCambridge, Witton, & Elbourne, 2014). If students and instructors know they are being studied, then the students might react differently in their study habits, test anxieties, etc., and instructors might teach in a different manner than normal (McCambridge et al., 2014), thus negatively impacting the study's internal validity (Seltman, 2015).

Researcher bias. If there is lack of objectivity on the part of the researcher, then bias is introduced into the research (Higgins et al., 2011; Yin, 2013). Since the researcher was a full-time faculty member in the business department of a participating college at the time of this research, the researcher did not use participants from his courses.

The following assumptions were accepted:

1. The demographics of the sample satisfactorily reflected the demographics of the population.

2. Participant responses were offered honestly, without bias, and reasonably represented the data the researcher attempted to collect.

3. The presumptions the researcher may have previously held about the information being studied did not significantly influence the outcome of the research.

Summary

Advancements in software and computer capabilities have made it possible to use computers as interactive teaching devices, and many journals, such as the *International Journal of Artificial Intelligence in Education* and *The Journal of Computer Assisted Learning,* contain a wealth of articles that affirm this new approach (Griff & Matter, 2013). Numerous researchers have conducted and reviewed studies in different disciplines, and the findings of the majority of these studies indicate student-learning increases from CAL and ALT programs (Cooke et al., 2008; John et al., 2009; Griff & Matter, 2013; Lee et al., 2011; Phillips & Johnson, 2011). With larger financial investments in ALTs at higher-education institutions in business courses, additional studies are needed to assess if ALTs are producing positive effects on student learning (Griff & Matter, 2013; James, 2012). Adaptive learning technologies have emerged to bring back the one-on-one learning environment that Bloom (1984) found to be significantly more effective than group learning. This study focused on an ALT, called LearnSmart, used in an introductory business course to see what outcome it had on unit exam scores.

Chapter Two contains a thorough review of adaptive learning. The origins of personalized learning and how ALT is derived from constructive learning, applied learning, and metacognition are presented. An evaluation of other studies in the field of adaptive learning are also explained.

In Chapter Three, the problem and purpose of this study are restated, and there is a review of the research questions and hypotheses that guided data collection and analysis. The majority of Chapter Three provides a comprehensive rationale for and description of the methodology employed in the study. Furthermore, the chapter contains a description of the population and sample studied, data collection methods, and data analysis procedures used in this study.

In Chapter Four, the results from this quantitative study on the impact of using the ALT, LearnSmart, in an introductory business course at higher-education institutions are presented and discussed. There is a review of the problem and purpose of the study as well as a summary of the instrumentation and data collection process. In addition, the findings from each research question are presented and explained.

In Chapter Five, the study is concluded with a summary of the research and data analysis. Recommendations are made for future classroom instructional strategies based on the results of the study. Suggestions for modifications to this study for additional future research are made in order to explore variations of ALT use at higher-education institutions.

Chapter Two: Review of Literature

Adaptive learning technology (ALT) uses a computerized-learning interface that continually assesses a student's metacognition to automatically personalize material for him or her (Fletcher, 2014; James, 2012). The ALT has been constructed from technological advancements in the fields of mathematics, algorithms, software development, hardware development, and education (Education Growth Advisors, 2014; Fletcher, 2013; Griff & Matter, 2013; McGraw-Hill Education, 2015, Webley, 2013). The use of ALTs has been adopted by classrooms teachers who seek to increase the one-on-one tutoring environment that Bloom (1984) found increased student learning two standard deviations over the long-standing traditional system of whole-group learning environments.

The invention of adaptive learning, sometimes referred to as personalized learning (Gallagher, 2014), stems from advancements in technology and from the need for teachers to better understand the learning habits of students in large classrooms (Education Growth Advisors, 2014). As more students are added to the classrooms of K-12 and higher education, teachers are less aware of how each student is learning (Garrison, 2011). Teachers are using adaptive learning technologies to change the situation, and proponents of adaptive learning say "technology has finally made it possible to deliver individualized instruction to every student at an affordable cost" (Fletcher, 2014, p. 64).

Higher education funding dropped sharply in a majority of states following the recession of 2009, and though many states have increased funding from those lower levels in recent years, most states are currently funding higher education at below pre-recession levels (Mitchell, Palacios, & Leachman, 2014). The state of Arizona, for example, cut higher-education funding per student by over 48% in 2009 (Mitchell et al., 2014). This cut in funding drove Arizona's education institutions into a mode of crisis, and one institution, Arizona State University, turned to adaptive technologies in order to bridge the gap between boosting student achievement and program cutbacks (Zimmer, 2014).

The results of the experiment at Arizona State University have been impressive, and the school now boasts an 18% increase in pass rates and a 47% drop in student withdrawals in remedial math courses (Education Growth Advisors, 2014). Since the funding levels at a majority of colleges have declined sharply, colleges are seeking alternative ways to accomplish educational goals. Adaptive learning technology is being used by instructors to help in this endeavor (Education Growth Advisors, 2014; Fletcher, 2014: Gallagher, 2014; Hopkins, 2014).

The Theoretical Foundation of Personalized Learning

At Oxford University a small group of three or four students are assigned to a primary professor who will educate, evaluate, and guide the small group through four years of academic instruction (Tight, 2012). These small groups are called tutorials, and while students take courses with other students and other professors in a larger context, each student must meet weekly with his or her primary professor to monitor his or her progress (Brookfield & Preskill, 1999). This one-on-one educational experience gives the primary professor a chance to become familiar with the knowledge of each student, and, if need be, give additional instruction to achieve a mastery level (Tight, 2012). The amount of time this process takes is significant, and the costs associated in providing such a personalized-learning situation are extremely high, but this instructional style leads to well-educated individuals (Dornisch, 2013). A number of educational theorists have advocated for the use of teaching in smaller groups to capture the learning opportunities that arise from having this specialized attention (Bloom, 1984; Brookfield & Preskill, 2012; Tight, 2012).

Another scenario of adaptive learning would be the specialized attention that home-schooled students or students enrolled in extremely small classes with diligent instructors receive. These extremely small classes exist in some K-12, higher education, and apprenticeship areas where an instructor can devote enough attention to personalize instruction to individual students (Tight, 2012). In these situations, a student who is performing poorly in one or multiple areas is given more attention and direction by the instructor in order to come up to par, and students who are performing at par might be given an opportunity to advance their learning through extra-credit work (Tight, 2012). As class size increases, the instructor's ability to determine which students are falling behind and which students are moving ahead quickly diminishes (Garrison, 2011).

At the crux of each of these scenarios is the instructor's ability to adapt the material to each student, thus the instructor is the adaptor (Horn, 2012). As the student-teacher ratio increases, instructors lose the ability to manage the amount of information needed to collectively increase the results of the entire group of students (Chew, 2014; Garrison, 2011). The next logical step is to add additional instructors in order to manage the cognitive load, but this increases costs for an institution to a point that is not feasible (Mitchel, Palacios, & Leachman, 2014).

Another issue to consider when adding additional teachers or sections of a course is that of learning-objective consistency (Cheeseman et al., 2007). The diligence and instructional-proficiency levels of teachers are not standardized (Shumow & Schmidt, 2013). The dedication and capacity of an instructor to effectively teach the subject matter varies substantially, resulting in an unequal presentation of information from classroom to classroom (Shumow & Schmidt, 2013). Creating a standard list of learning objectives for each course with teachers who can effectively teach to those standards is difficult (Cheeseman et al., 2007). Students who find themselves in the classrooms of underperforming teachers often demonstrate inadequate skills to progress to higher-level courses (Cheeseman et al., 2007). The inconsistencies that exist create a need for the development of learning-objective standardization and instructional standardization, in order to ensure topics are effectively presented and taught (Shumow & Schmidt, 2013). Technology is now being used to ensure course consistency and standardization (Education Growth Advisors, 2014; Fletcher, 2013; McGraw-Hill Education, 2015, Webley, 2013).

In years past, educational technology was met with steep opposition by many institutions due to its lack of effectiveness and high cost (Bain & Weston, 2012; Huntsberry, 2015; Reich, 2014; Webley, 2013). The hardware needed to implement the software was expensive, required frequent replacement, and relied heavily on instructors to teach students how to use it (Fletcher, 2013). The software programs were marginally effective and could not be used outside a specific physical location; hence, accessibility was an obstacle (Waters, 2014). These three items: cost, quality, and accessibility became known as the “Iron Triangle” (Education Growth Advisors, 2014, p. 2), and for decades this fortress was impenetrable (Waters, 2014). As technology developed and became more widely used, the issues of cost and accessibility lessened (Hickman, 2013;

Huntsberry, 2015). The issue of quality is still the major concern, and it is to this concern the focus of adaptive learning technology is directed (Dietvorst et al., 2014; Dornisch, 2013; Education Growth Advisors, 2014; Fletcher, 2014; Horn 2012; Huntsberry, 2015; Riddle, 2013; Waters, 2014; Webley 2013; Zimmer, 2014).

Adaptive learning utilizes the concept of personalized learning, which is instruction that is dependent on the learner to set the pace of instruction and the subject matter sequence (Fletcher, 2013). In personalized learning, the objectives, the approaches to instruction, and the content of what the learner encounters next is based on the performance and needs of the learner (Fletcher, 2013; Tomlinson, 2014). Personalized learning creates an environment that stems from active learning, thus learning becomes more interest-based, self-directing, and meaningful (Fletcher, 2013; Tomlinson, 2014).

Adaptive learning technology differs from technology-enhanced personalized learning, because adaptive learning technology relies heavily on the use of algorithms to determine future courses of action for the student rather than the student having full control of the direction and sequencing of the material (Fletcher, 2013). Algorithms are broadly defined as step-by-step procedures for solving a problem or accomplishing some end (Gullapalli & Brungi, 2015). Algorithms are a series of contingencies that have specific actions and are used to do everything from solving a Rubiks Cube™ to determining what time of the day students are most likely to best learn mathematics (Hickman, 2013). Algorithms are similar to recipes in that they contain a set of instructions in sequential patterns predicated on contingencies (Dietvorst et al., 2014; Gullapalli & Brungi, 2015; Hickman, 2013). Algorithms are tested and refined with large amounts of data points in order to ensure their effectiveness (Dietvorst et al., 2014; Gullapalli & Brungi, 2015; Hickman, 2013).

Algorithms can be used to make predictions regarding: weather; which people are most likely to break the law and the time of day they will break the law; when students learn best; what types of individuals would best learn computer science; or how many car accidents will occur in a given day (Dietvorst et al., 2014; Hickman, 2013). Algorithms have been proven to be more accurate at predicting such events; therefore, algorithms are now applied to metacognition and ALTs to increase learning (Dietvorst et al., 2014; Hickman, 2013). Algorithms can also be used to inform students of information they know compared to information they do not know so students can constructively learn the things they do not know (Hickman, 2013). In the field of education, ALT uses algorithms to create a personalized learning path for each student, thus specifically addressing each student's needs and goals (Klasnja-Milicevic et al., 2011).

The Learning Theories Behind Adaptive Learning

The science of learning is a systematic and empirical approach to understanding how people learn (Mayer, 2011). More formally, Mayer (2011) defined the science of learning as the "scientific study of how people learn" (p. 3) and the science of assessment as the "scientific study of how to determine what people know" (p. 3). Collectively, the sciences of learning and assessment encompass the learning, remembering, and transferring of knowledge during and after instruction to help one determine the successfulness of instructional methods (Engestrom, 2014; Mayer, 2011).

Learning could be broadly defined as "internalizing the representational and communicative means of the subject discourse" (Engestrom, 2014, p. 51). The learning theories that underpin traditional learning include cognitive development theory, knowledge construction, and knowledge representation (Pange & Pange, 2011). In addition to traditional learning theories behind adaptive learning, some researchers believe there is a new theory, e-learning theory, that has been emerging due to technology advancements (Haythornthwaite & Andrews, 2011). E-learning uses electronic devices to deliver educational content via instructional methods to build knowledge and promote learning (Haythornthwaite & Andrews, 2011). Adaptive learning technologies are built upon the theories of constructivism, applied learning, and metacognition (Gallagher, 2014).

The Role of Constructivism in Adaptive Learning

Cognitive development was theorized by psychologist Jean Piaget (1972) in the mid-twentieth century and is an exhaustive study involving the cognitive development process of infants to adults. Piaget (1972) concluded humans learn from hands-on activities of trial and error, and finding error in preconceived ideas leads to a deeper understanding. His work ultimately can be divided into two parts: assimilation and accommodation (Isaacs, 2015; Müller et al., 2015; Piaget, 1972). Assimilation is the adaptation of new ideas or concepts (Isaacs, 2015; Müller et al., 2015). When a person is exposed to something he or she did not know before, then that person must begin to figure out how this new information fits into his or her preconceived idea (Illeris, 2015). Assimilation represents an initial form of learning (Piaget, 1972). Piaget (1972) developed sub-stages of learning in order to define how an infant gains an understanding of the world around him or her (Illeris, 2015). When new information is presented, the infant must learn how to work with this new construct (Illeris, 2015). Once the infant concludes this new information has altered his or her understanding of reality, then accommodation usually occurs in order to make the new information part of his or her schema (Piaget, 1972).

Knowledge construction is another piece of the learning process (Pange & Pange, 2011). Reality is slightly different for each individual, and through a life-long process of cognitive development, one begins to piece information together into a unified multi-part, cohesive understanding (Lucas, Gunawardena, & Moreira, 2014). According to constructivism theory, all knowledge is constructed by an individual through the reality that exists for that individual, and instruction reshapes that individual's understanding of reality (Byrnes, 2013). Because this phenomenon of learning is a discovery process, the act of being incorrect and acknowledging the error is part of the constructive learning process (Byrnes, 2013). If an individual never experiences new information or never acknowledges he or she is incorrect, then learning cannot take place (Chew, 2014).

The theory of cognitive development is also bolstered by complementary theories of learning from Engestrom and Vygotsky (Engstrom, 2014). Engestrom's (2014) activity theory is based on a person's ability to try, fail, and try again to help gain understanding, and Vygotsky's work on the transference of moving understanding from the social plane to the internal plane, both lead to conclusions that learning comes largely from the outside in (Byrnes, 2013). James Byrnes (2013), a leading cognitive-development theorist in the 21st century, has found three key threads that simplify how assimilation and accommodation work from an operational perspective. The key threads are: how the base knowledge of a person was acquired before beginning the activity, the activity itself having meaning with a defined goal, and the repetition of the activity (Byrnes, 2013).

Knowledge representation is "most fundamentally a surrogate, a substitute for the thing itself, used to enable an entity to determine consequences by thinking rather than acting, i.e., by reasoning about the world rather than taking action in it" (Davis, Shrobe, & Szolovits, 1993, p. 1). Artificial intelligence uses knowledge representation in order to create symbols that represent the objects themselves (Bench-Capone, 2014). For example, if a computer program were to represent an oak tree, it would show a picture or symbol of the closest example of an oak tree (Burton-Jones & Grange, 2012; Davis et al., 1993). The tree, of course, is not real, but the picture is a substitute to convey the meaning, and if another picture is shown of a maple tree, the observer would probably still categorize it as a tree (Burton-Jones & Grange, 2012; Davis et al., 1993). During the assimilation process, humans categorize new objects with those of which they are familiar (Burton-Jones & Grange, 2012; Davis et al., 1993). Because ALT uses computers to convey the meaning of words and objects, the closer the representation of the object itself the better the conveyance will be (Bench-Capone, 2014).

Adaptive learning technology encompasses all three underpinning elements of constructivism: cognitive development theory, knowledge construction, and knowledge representation (Gallagher, 2014; James, 2012, Pange & Pange, 2011). Since ALT is personalized to each individual student, the platform in which each person begins to learn is equal, unlike the traditional, seated classroom environment (Klasnja-Milicevic et al., 2011). Each student brings a different base knowledge acquired through different learning styles and in different ways, thus each student will ultimately experience new information that will lead to assimilation (Illeris, 2015; Isaacs, 2015). The student will naturally try to make an attempt at accommodation (Piaget, 1972; Ultanir, 2012).

Because ALT uses algorithms to predict knowledge, students are able to have a personalized learning experience that ultimately guides them through a constructivist pedagogy in order to learn the material (NEJM, 2014). Since ALTs use practice and repetition to learn the information, accommodation should occur (NEJM, 2014; Piaget, 1972). Because ALT is delivered by a computer, the adaptation of different learning styles can be achieved (Akbulut & Cardak, 2012; Fletcher, 2013; Haythornthwaite & Andrews, 2011; Reich, 2014; Waters, 2014; Webley, 2013; Zimmer, 2014). Information may be delivered in different styles of text, animation and other visual methods, audio recordings and readings, kinesthetic activities of clicking, dragging, and movement of objects, manipulation of various parts, and the manipulation of the environment of the student (Akbulut & Cardak, 2012; Fletcher, 2013; Waters, 2014; Webley, 2013). Students may be in a classroom or at home or in hotter and colder environments or in brightly-lit or dimly-lit environments (Akbulut & Cardak, 2012). Adaptive learning technology is mobile, thus traditional limitations of the classroom fall away (Akbulut & Cardak, 2012).

The Role of Active Learning in Adaptive Learning

Furthermore, adaptive learning is supported by active learning (Engestrom, 2014; Freeman et al., 2014; Gallagher, 2014; Huntsberry, 2015; Jensen et al., 2015). Researchers have indicated that in the attempt to educate children or adults, providing isolated lectures often does not improve learning (Jensen et al., 2015; Lord et al., 2012). Learning can and is accomplished through lectures, but researchers argue this is because learning results from students having negotiated with the subject matter on their own first (Jensen et al., 2015). This process is known as cognitive structuring (Schwartz & Goldstone, 2015).

Active learning involves the actions students take in an attempt to learn beyond merely listening to a lecture, taking notes, or thinking about the information they are trying to learn (Freeman et al., 2014; Lord et al., 2012). The concept of active learning requires the students to have a hands-on experience with the material in order to be actively engaged in the learning process (Freeman et al., 2014; Jensen et al., 2015). Active learning is similar to kinesthetic learning, in which students are physically accomplishing a task, but active learning does not necessarily require the same level of physical activity as kinesthetic learning (Lord et al., 2012).

Since there is a level of interaction and engagement with the subject matter, active learning brings the student closer to understanding what he or she knows and does not know (Freeman et al., 2014; Lord et al., 2012). Researchers support the positive connection between higher-levels of student engagement with the material and increased learning, and student engagement has been proven to be a significant predictor of learning (Quaye & Harper, 2014). Students who are engaged with the material often perform better, and this results in students taking control of their own learning (Chew, 2014; Tanner, 2012).

When a student is asked to engage with the material or with information, he or she is able to learn more than when merely being presented passive types of learning opportunities (Bertsch & Pesta, 2014; Engestrom, 2014; Freeman et al., 2014; Jensen et al., 2015; Van Blerkom, Van Blerkom, & Bertsch, 2006). In psychology, these concepts are tested as an experimental finding called the *generation effect* or generation advantage (Bertsch & Pesta, 2014). The generation effect is the "experimental finding that when a subject is asked to generate all or part of a stimulus item, that item is almost always remembered better than material the subject only read" (Bertsch & Pesta, 2014, p. 77). The size of the generation effect is computed by taking the proportion of the number of previously generated items to the previously read items that were remembered (Bertsch & Pesta, 2014). Researchers found information is more likely to be remembered under conditions that require learners to produce, or generate, some or all of the material themselves, versus reading what others had prepared (Bertsch & Pesta, 2014; Jensen et al., 2015). The unknown piece of information in active learning is which types of active learning techniques are the most effective for different types of subjects and objectives (Freeman et al., 2014; Jensen et al., 2015). Researchers evaluating ALTs seek to find the same information, the types of active learning techniques that are most effective for different types of subjects and objectives (James, 2012; Griff & Matter, 2013).

The basic idea students learn more when they spend effort and energy on learning the material opposed to putting forth little energy is supported by researchers, but the amount of energy required by the student in order to increase learning is still an area of research (Bertsch & Pesta, 2014; Chew, 2014; Engestrom, 2014; Freeman et al., 2014; Gallagher, 2014; Huntsberry, 2015; Jensen et al., 2015; Lord et al., 2012; Tanner, 2012; Van Blerkom et al., 2006). In 2007, a meta-analysis of 86 simple generation effect studies was analyzed, and researchers found students who were required to produce or generate at least a part of the material when studying performed an average of 66% higher on assessments covering the material (Bertsch & Pesta, 2014). The researchers concluded active assessment-preparation assignments are more effective than passive assessment-preparation assignments (Bertsch & Pesta, 2014).

Assessment-preparation assignments that required students to produce full sentences of material in context yielded the highest results, but even assessment-preparation assignments that required students to merely generate one letter that was missing from a word yielded better results than assignments that required only reading (Bertsch & Pesta, 2014). Seventy-three percent of students who were required to generate full sentences of material in assessment-preparation assignments scored higher than students who were asked to only read the material, and 64% of students who were required to generate only one letter or rearrange letters in words in assessment-preparation assignments scored higher than students who were asked to only read the material (Bertsch & Pesta, 2014). When analyzed, students who were asked to generate missing words through rhyming a word presented to them in assessment-preparation assignments scored 68% higher than students who only read the information (Bertsch & Pesta, 2014).

Students who were given a synonym as a hint to generate a missing word in assessment-preparation assignments scored 66% higher than students who only read the information (Bertsch & Pesta, 2014). Sixty-nine percent of students 65 years and older who were asked to generate any portion of the material in assessment-preparation assignments scored higher than the average of all students who were asked to only read the material for assessment-preparation (Bertsch & Pesta, 2014). Sixty-six percent of students under the age of 65 years old who were asked to generate any portion of the material in assessment-preparation assignments scored higher than the average of all students who were asked to only read the material for assessment-preparation (Bertsch & Pesta, 2014).

Another interesting piece of information is that 74% of students who were asked to generate any portion of the material in assessment-preparation assignments more than one day before taking the assessment scored higher than the average score of students who were asked to only read the material one day before taking the assessment, indicating retention is increased when the student is asked to actively engage and interact with the material (Bertsch & Pesta, 2014). With 66% of students being asked to generate any piece of information of the material in assessment-preparation assignments scoring higher than their counterparts who were asked to partake in passive learning exercises, additional research needs to be conducted to find out what specific techniques of assessment-preparation assignments work better than others (Bertsch & Pesta, 2014). When surveyed, students often admit to studying for assessments by reading the information, highlighting information in the textbook or on their notes, outlining the information in the textbook, and writing practice questions on paper and note cards in the form of full sentences or key words (Chew 2014; Bertsch & Pesta, 2014). The most active form of learning from the list of study techniques listed previously is the one in which students actively write practice questions (Lord et al., 2012).

In order to study new material, a student might create the question, "What are the five factors of production?" to ask himself or herself later while studying for an assessment, and then the student might go about trying to recall the information and answer the question (Bertsch & Pesta, 2014, p. 74). The effectiveness of this type of study technique was analyzed in 2006 by comparing test scores covering a passage on locus of control between four different groups of students: one group read the text and copied it, the second group read the text passage and highlighted the areas they found to be important, the third group read the text passage and took notes on the items they believed were important, and the last group read the textbook passage and wrote down different test questions they believed would be asked during the assessment (Van Blerkom et al., 2006). Out of the results from the experiment, two key pieces of information were noticed by the researchers: the students who read the text and wrote down questions on items they believed would be on the assessment received the highest scores on the assessment, and students were not effective at determining what information was important from the textbook or from their notes (Van Blerkom et al., 2006). Out of all the questions students wrote down as potential assessment questions, only about 40% of those questions were actually important enough to be on the assessment created by subject matter experts (Van Blerkom et al., 2006).

In another experiment cited by Bertsch and Pesta (2014), students who created and wrote down their own practice questions from textbook material answered those same questions correctly 86% of the time compared to students who were given practice questions from an instructor. The students who were given practice questions from their instructors answered 72% of the questions correctly (Bertsch & Pesta, 2014). It would appear students who are asked to write down their own potential assessment questions would score higher overall on exams, but students miss correctly targeting about 80% of the information that is actually important (Bertsch & Pesta, 2014).

The overarching problem is students are not able to figure out which pieces of information are more important than others when reading or being exposed to new information (Bertsch & Pesta, 2014; Chew, 2014; Kobayashi, 2005; Tanner, 2012). When students are asked to take notes while reading, only about 15% of the ideas instructors deem to be important are noted in the students' notes, once again indicating students are unclear as to how to decipher important information (Bertsch & Pesta, 2014). In a review of 57 different studies on the impact of note-taking, Kobayashi (2005) found only slightly more than 50% of students taking notes scored higher than students who did not take notes. Students fail to determine what information is important when learning new material, and they need to either be told what information is important or they must learn to figure out how to determine what information is important (Chew, 2014; Bertsch & Pesta, 2014; Kobyashi, 2005; Tanner, 2012; Van Blerkom et al., 2006).

Instructors are left to decide how to teach in the most effective manner in order to increase student learning (Chew, 2014; Bertsch & Pesta, 2014; Kobyashi, 2005; Tanner, 2012; Van Blerkom et al., 2006). If the instructor does not require any form of active learning assignment, then students who take notes will probably not accurately assess which information is important (Kobayashi, 2005). If the instructor decides to give students his or her notes in complete form, the instructor runs the risk of students not engaging with the material in an active way which leads to lower performance on assessments (Chew, 2014; Engestrom, 2014; Freeman et al., 2014; Gallagher, 2014; Huntsberry, 2015; Jensen et al., 2015; Lord et al., 2012; Tanner, 2012). Instructors could select to mesh both options together and give students a partially complete set of notes. Students would then have the information that is important and be actively engaged by completing the notes by generating the missing information (Chew, 2014; Bertsch & Pesta, 2014; Kobyashi, 2005; Van Blerkom et al., 2006).

One experiment conducted in 2003 involved an instructor giving some students a set of notes that contained only pieces of key information pertaining to the information that was covered in the lecture and text (Katayama & Crooks, 2003). The rest of the students received a complete set of notes containing key information on the lecture and text (Katayama & Crooks, 2003). At the end of the lecture, students completed an assessment containing different types of questions (Katayama & Crooks, 2003). The same assessment was given one week later (Katayama & Crooks, 2003). The students who were given the partial set of notes scored higher on both assessments; thus retention was increased with the active-learning, generation technique (Katayama & Crooks, 2003). Instructors could effectively increase learning by putting the student in the position of having to complete, manipulate, or source the information for themselves, which would lead to higher-levels of generation (Bertsch & Pesta, 2014). Adaptive learning technology is supported by active learning and generation since students are required to interact with the information and often generate pieces of information about the material while completing the exercise (McGraw-Hill Education, 2015; NEJM, 2014).

The Role of Metacognition in Adaptive Learning Technology

Metacognition is the attention paid to monitoring and directing one's own thinking (Chew, 2014). Metacognition could be further defined as peoples' abilities to predict their performances on various tasks based on confidence levels and other internal inputs in order to adjust the amount of information needed from an instructor in the future (Chew, 2014). Students gain understanding from metacognition, because metacognition allows students to form their own assessment of knowledge, assess what they do and do not know, and then make additional decisions based on this knowledge (Chew, 2014; Kilgo et al., 2014). When a student takes part in an assessment over a particular subject, then he or she starts by determining how confident he or she feels in the knowledge he or she has prior to taking the assessment (Butler & Winne, 1995; Chew, 2014; Kilgo et al., 2014). If the student feels unprepared for the assessment, then he or she might seek additional study to remedy the situation (Chew, 2014). Once the assessment is complete, the student then analyzes the results to determine if more study is needed in a particular area (Chew, 2014).

Researchers studying the process of learning support the idea students perform at higher levels when they have higher metacognitive awareness compared to students who have lower levels of metacognitive awareness (Roll, Wiese, Long, Aleven, & Koedinger, 2014). In addition, students who are able to self-regulate their learning process are able to form personal goals and are more likely to meet objectives (Bjork, Dunlosky, & Kornell, 2013). The ability for a student to self-regulate or self-monitor builds upon traditional cognitive learning theories and creates a foundation for metacognitive theory (Bjork et al., 2013; Chew, 2014). Because of the increase in student learning from metacognitive awareness, developing higher levels of metacognitive awareness has been marked by the U.S. Department of Education as a primary focus for students in the future (Anderman, 2011).

Metacognitive knowledge can be divided into three key areas of self-knowledge, contextual knowledge, and strategic knowledge (Anderson & Krathwohl, 2001). Self-knowledge is the ability for a person to understand his or her own skills, abilities, and strengths (Chew, 2014). The concept of self-knowledge also includes the ability for a person to know when he or she does not know certain information and then seek out this information through internal motivation (Chew, 2014). Contextual knowledge relates to cognition and is defined as the ability of a person to evaluate the difficulty of tasks and make corrections and changes in the approach to learning the task (Anderson & Krathwohl, 2001). Strategic knowledge can be described as the skills a learner manages, directs, and self-regulates in an attempt to learn (Anderson & Krathwohl, 2001). The approach to metacognitive strategic knowledge is guided by the learner's ability to position information in correct order so the information can be recalled in the future to accomplish an objective (Tanner, 2012).

Adaptive learning relies primarily upon the metacognitive subsets of self-knowledge and strategic knowledge (Chew, 2014). Self-knowledge is important to discuss, because students enter a learning environment with different levels of knowledge, different skills and abilities, different experience levels, and different strengths and weaknesses (Anderson & Krathwohl, 2001). The unique individuality of each student presents challenges for whole-group learning environments, which are often unable to adapt to individual student needs (Anderson & Krathwohl, 2001). The metacognitive self-knowledge levels of the students vary greatly in whole-group learning environments (Anderson & Krathwohl, 2001; Chew, 2014; Tanner, 2012). A major focus is in place by educators to increase student understanding of metacognition (Anderman, 2011). Metacognitive strategic knowledge is important, because students need to be able to determine how to sequence information in an order that can be recalled later in a way that is understandable (Anderson & Krathwohl, 2001). A student must have an internally-motivated strategy within himself or herself to effectively engage and learn the material for mastery, and this strategy includes the use of self-monitoring (Chew, 2014; Tanner, 2012).

Self-monitoring includes the ability for a student to regulate his or her environment, goals, time management, and knowledge acquisition (Chew, 2014). Because self-monitoring requires self-regulation, the terms self-monitoring, self-regulation, and metacognition are often used interchangeably (Tanner, 2012). Self-regulation and self-monitoring could not exist without metacognition, because in order for a student to gain an accurate assessment of his or her understanding, he or she must engage in the act of determining what he or she currently knows (Chew, 2014). The thoughts and actions a student takes in determining his or her current knowledge level is metacognition (Tanner, 2012).

Self-monitoring requires a person to plan, organize, control, schedule, and seek ways to accomplish goals (Bjork et al., 2013). Students demonstrate metacognitive abilities when they are able to create new strategies to achieve goals in different situations (Bjork et al., 2013). Metacognitive abilities correlate to higher learning outcomes, but often students do not know how to use metacognition, and need more instruction in metacognition (Kilgo et al., 2014). Software programs with advanced technology, such as ALTs, are delivering metacognition instruction to students in order to help them achieve a better understanding of how to use their own metacognition to learn more (McGraw-Hill Education, 2015). These software programs are helpful to students as they regulate the pace of instruction and build upon the theory of cognitive scaffolding to learn more efficiently (McGraw-Hill Education, 2015; Waters, 2014).

Adaptive learning technology breaks the mold of traditional teaching strategies that are designed for whole-group learning (Waters, 2014). Adaptive learning technology enables personalized learning through the use of metacognition and cognitive scaffolding (McGraw-Hill Education, 2015; NEJM, 2014; Waters, 2014). Clark and Feldon (2014) classified ALT in the field of multi-media technology learning, which includes any technology used to present or give instruction (Clark & Feldon, 2014). Multimedia also could be more broadly defined as the capacity of computers to provide real and simulated video and audio instruction through the use of images, video, audio and animation (Clark & Feldon, 2014). Bain and Weston (2012) concluded the mere addition of technology to the learning curriculum does not always produce an increase in learning, even though many of the additions include exercises that involve the use of active learning and other educational theories. The research findings that Clark and Feldon (2014) offered are consistent with Bain and Weston (2012) and indicate the addition of technology and multimedia to the classroom must be accompanied by teaching strategies designed to maximize the learning opportunities offered through the technology.

Multimedia and Adaptive Learning Technology

In their paper, “Ten Common But Questionable Principles of Multimedia Learning,” Clark and Feldon (2014) offered 10 educational instructional strategies educators commonly believe to be true when adding technology to the classroom. The list was compiled through years of research on studies that used multimedia technology instructional tools used in the classroom (Clark & Feldon, 2014). The first commonly believed notion is that “multimedia produces more learning than do live teachers or older media such as textbooks or television” (Clark & Feldon, 2014, p. 152). Researchers have found no credible evidence to support the notion multimedia presentations today are dramatically different from those of the past, thus additional research is needed in this field (Clark & Feldon, 2014).

The second commonly believed notion is that “multimedia instruction is more motivating than other instructional media” (Clark & Feldon, 2014, p. 153). It is true many students find multimedia instruction and presentations to be more engaging and entertaining, but little evidence exists from previous research to conclude that additional learning results from multimedia instruction (Clark & Feldon, 2014). Reih, Kim, and Markey (2012) noted less learning could result given longer exposure to the multimedia instruction.

The third commonly believed notion is that “multimedia instruction provides animated pedagogical agents that aid learning” (Clark & Feldon, 2014, p. 154). Multimedia additions in various forms have offered little in the way of any pedagogical agents that aid in learning (Clark & Feldon, 2014). The use of televisions, audio devices, and other forms of multimedia devices do not offer differences in pedagogies, as that would be the work of the instructor or the developers of the material being displayed or played (Clark & Feldon, 2014).

The fourth commonly believed notion is that “multimedia can effectively teach to different learning styles” (Clark & Feldon, 2014, p. 155). Researchers have investigated the connection between learning styles and increases in learning for many years, and there is little evidence to support a connection exists (Clark & Feldon, 2014). A meta-analysis of learning styles research compiled in 2009 by Pashler, McDaniel, Rohrer, and Bjork concluded:

> Although the literature on learning styles is enormous, very few studies have even used an experimental methodology capable of testing the validity of learning styles applied to education. Moreover, of those that did use an appropriate method, several found results that flatly contradict the popular meshing hypothesis… We conclude therefore, that at present, there is no adequate evidence base to justify incorporating learning styles assessments into general educational practice… Thus, limited education resources would better be devoted to adopting other educational practices that have a strong evidence base, of which there are an increasing number. (p. 105)

Researchers are compiling additional evidence to support the argument that no strong correlations exist between learning and learning style (Clark & Feldon, 2014).

The fifth commonly-believed notion is that "multimedia instruction facilitates student-managed constructivist and discovery approaches that are beneficial to learning" (Clark & Feldon, 2014, p. 157). Researchers conceded multimedia instruction incorporates a certain level of student-managed constructivist and discovery approaches (Clark & Feldon, 2014). Although multimedia instruction includes these discovery approaches, due to the vast array of previously acquired information that exists amongst students, it is not conclusive to lend the gains in learning solely to the multimedia device (Clark & Feldon, 2014).

The sixth commonly believed notion is that "multimedia instruction provides students with autonomy and control over the sequencing of instruction" (Clark & Feldon, 2014, p. 158). Several multimedia devices allow for the manipulation of the sequence of instruction, time, and selection of material to be made by the learner, but the vast majority of multimedia devices do not allow for this autonomy (Clark & Feldon, 2014; Waters, 2014). Researchers investigating multimedia instruction from devices that do not allow for student control have concluded there are no significant gains to be had through the use of the technology, but more research is needed on devices that allow for the manipulation of the variables described above (Clark & Feldon, 2014). Researchers note students who use multimedia devices that allow for the manipulation of time, sequence of material, and other options can experience cognitive overload, thus leading to a decline in learning (Chew, 2014; Clark & Feldon, 2014).

The seventh commonly believed notion is that “multimedia instruction allows students the opportunity to practice critical and higher-order thinking” (Clark & Feldon, 2014, p. 159). Higher-order thinking is defined as an inclination toward thoughts that are constructed with intention toward the outcome involved (Lee, 2015). An example of higher-order thinking would include the decision of a student to go to Harvard University, because he or she believed Harvard had the best program available in his or her area of study and Harvard also fostered a more compatible social environment (Clark & Feldon, 2014). A student practicing lower-order thinking might not put forth additional effort in the decision and choose to go to Harvard merely because he or she was not aware of any other options (Clark & Feldon, 2014). In a 2015 meta-analysis of more than 100 studies, Abrami, Bernard, Borokhovski, Waddington, Wade, and Persson found no link between multimedia instruction and learning outcomes. The researchers support their claim that critical thinking occurs when the instruction involves defined learning objectives presented to the students by well-trained instructors, and not enough evidence exists to credit multimedia instruction with increased learning (Abrami et al., 2015).

The eighth commonly believed notion is that "multimedia instruction provides incidental learning of enriching information" (Clark & Feldon, 2014, p. 161). Incidental learning includes learning that takes place by chance or by a series of undirected events (Clark & Feldon, 2014). There is not enough empirical evidence to support the belief learning can happen by chance or through proximity of a multimedia device, but rather learning occurs through dedicated, strategic actions by the learner (Clark & Feldon, 2014).

The ninth commonly believed notion is that "multimedia instruction offers an increased level of interactivity with the material" (Clark & Feldon, 2014, p. 163). Interactivity, as defined in context to multimedia instruction, includes immediate feedback provided to students when answering questions or submitting answers, explanations of errors made, and providing principle-based hints to students who are performing poorly (Clark & Feldon, 2014). Roll, Wiese, Long, Aleven, and Koedinger (2014) stated, "evidence is mounting that students are not good at seeking assistance or information at the right time" (p. 170), and students need additional help in learning when to seek additional study aids. It is widely accepted multimedia instructional devices tend to have increased levels of student interactivity with the material; therefore, active learning theorists are credited with the accomplishment of finding this connection (Clark & Feldon, 2014; Freeman et al., 2014; Jensen et al., 2015; Lord et al., 2012). However, due to the large number of multimedia instructional devices in use, researchers have not been able to attribute learning advantages to all forms of multimedia instruction, which raises questions about which methods and devices impact learning (Clark & Feldon, 2014). All forms of interactivity have not been proven to be effective at increasing learning; therefore, attributing credit to a tool's interactivity is suspect (Clark & Feldon, 2014).

The tenth commonly believed notion is that "multimedia instruction permits students to experience an authentic learning environment and activities" (Clark & Feldon, 2014, p. 165). The researchers define an authentic learning environment similar to that of a situated learning where the learner can effectively transfer his or her surroundings to the actual environment that is trying to be replicated, such as that of flight simulators (Clark & Feldon, 2014; Jonassen & Land, 2012). The objective of authentic learning is that transfer will take place if the learning environment is similar to that of the application environment (Clark & Feldon, 2014; Jonassen & Land, 2012).

Researchers in the early 1900s presented evidence of authentic environment and situated learning theory in studies where learning environments were similar to application environments (Thorndike & Woodworth, 1901). Thorndike and Woodworth (1901) named their theory "identical elements" (p. 386), and this later became known as a core principle in the situated learning theory (Jonassen & Land, 2012). Researchers still question the amount of identical elements needed in learning environments and application environments to effectively allow for transfer to take place, but many multimedia devices, such as televisions, projectors, and audio equipment offer little in the way of identical elements to application environments (Clark & Feldon, 2014). Researchers agree there is insufficient research available to conclusively agree if the addition of any multimedia instructional tool will increase learning, but multimedia offers significant benefits for education in some situations (Clark & Feldon, 2014).

As previously explained, educators have misconceptions about the effectiveness of adding technology to the classroom (Abrami et al., 2015; Bain & Weston, 2012; Clark & Feldon, 2014; Freeman et al., 2014; Jensen et al., 2015; Lord et al., 2012; Roll et al., 2014), but research has been conducted and researchers indicate faculty are the ones who decide whether to add and implement technology (Turner, Kitchenham, Brereton, Charters, & Budgen, 2010). A variety of factors are cited by faculty when deciding to add technology to the classroom, such as ease of use, cost, and effectiveness, but one factor, the willingness for instructors to accept technology, is central to the decision (Turner et al., 2010). The use of technology in the classroom is linked to the instructor's willingness to accept technology in the classroom as a whole, and the ease of use of the technology being considered did not necessarily mean the technology would be used (Turner et al., 2010). Instructors need to be willing to use the technology, and the technology needs to be easy to use (Turner et al., 2010). Researchers also noted a trend in the data indicating if the instructor was comfortable with the technology, then the cost of the technology became less important to him or her (Turner et al., 2010).

Adaptive learning technologies make use of personalized learning for each student through the use of metacognition, constructivism, and active learning (Gallagher, 2014), but another technology, the *clicker*, was created years before ALTs, and clickers build on similar learning theories (Manke-Brady, 2012). Clickers are a system of hand-held voting devices often used in large classrooms at higher-education institutions in order to poll students on the information being covered (Manke-Brady, 2012; Stowell, 2015). Instructors create multiple-choice questions for the students and either ask the question verbally or post the question through a projected device (Stowell, 2015). Students then select their response by pushing the corresponding button on the clicker (Stowell, 2015). The student remains anonymous to other classmates, but the instructor has the option to know how each student answered (Stowell, 2015). Instructors frequently are unaware of which students lack understanding of the material during class, because many students are too embarrassed to raise their hands and ask questions (Manke-Brady, 2012; Stowell, 2015). The clicker system of polling adds to the instructor's knowledge of how the class as a whole is progressing, but using the clickers does little in the way of informing the instructor about the knowledge level of each student (Manke-Brady, 2012; Stowell, 2015).

Instructors who use clicker systems are able to gather immediate data about their students and readjust and adapt as necessary to tailor the material to better meet the needs of the students (Manke-Brady, 2012; Stowell, 2015). There have been numerous studies on clicker devices in classrooms in the last decade, and the results of the impact of clickers on learning are mixed (Gunn et al., 2015; Keough, 2012; Manke-Brady, 2012; Stowell, 2015). Researchers agree using clickers increases active learning and the interaction between the instructor and his or her students, as engagement levels were elevated in many of the studies (Keough, 2012; Stowell, 2015). Keough (2012) reviewed 66 previous clicker studies focused on student perceptions and outcomes. Keough (2012) determined that high levels of "actual performance, perceived performance, student attention span, attendance, and participation, as well as student perceptions of satisfaction, feedback, and ease of use" (p. 105) were all apparent in the cross-discipline studies. Keough (2012) then replicated the study in the management discipline and found similar results. Student engagement has been proven to be a significant predictor of learning (Quaye & Harper, 2014), so technology options that increase engagement are actively being researched.

When the instructor is changing and altering curriculum to meet the needs of students, then he or she is placed in the role of an adaptor. The major difference between clicker technology and ALTs is that ALTs use computers and algorithms to assume the role of the adaptor of instruction instead of a human (Fletcher, 2013; Gallagher, 2014; Horn, 2012; McGraw-Hill Education, 2015; Waters, 2014; Webley, 2013). When the ALT assumes the role of the adaptor, artificial intelligence is used to create the personalized path of instruction for the student (Fletcher, 2013; Gallagher, 2014; Horn, 2012; McGraw-Hill Education, 2015; Waters, 2014; Webley, 2013)

Adaptive Learning Technology Options

There are several major ALT companies that exist, and most of their technology is licensed by publishers to use along with established textbooks (Riddell, 2013). As of August, 2013, there were over 70 different ALT companies (Fletcher, 2013). The companies that are notable in the field with published results include: McGraw-Hill Education Education's Area 9, Knewton, Smart Sparrow, SnapWiz, and DreamBox Learning (Riddell, 2013). Each system uses its own proprietary algorithms in order to predict knowledge levels, thus the technology driving each system is essentially the same (Education Growth Advisors, 2014; Fletcher, 2013; Horn, 2012; James, 2012; Riddell, 2013; Waters, 2014; Webley, 2013). There are slight user interface differences from one system to another, and the questions and probes are usually text specific, but each company claims to have greater success by having better algorithms (McGraw-Hill Education, 2015; Riddell, 2013). In order to determine which ALT is best, studies are emerging from different companies and educational institutions (Cooke et al, 2008; Education Growth Advisors, 2014; Huntsberry, 2015; James, 2012; McGraw-Hill Education, 2015; Waters, 2015).

The large-scale program that has been on the market since 2004, is McGraw-Hill Education's Area 9 product called LearnSmart (McGraw-Hill Education, 2015). LearnSmart is used in numerous disciplines, and it is primarily used at higher-education institutions in the United States (McGraw-Hill Education, 2015; NEJM, 2014). Since LearnSmart encapsulates the adaptive learning and educational learning theories highlighted in this study, focus will be placed on this ALT tool for the latter (McGraw-Hill Education, 2015). LearnSmart was developed by Ulrik Christiansen, a medical doctor who set out to develop a learning tool that would reduce the number of errors medical doctors make under pressure (NEJM, 2014).

Christiansen practiced medicine for a number of years and noticed doctors were making elementary errors at different points during operations (NEJM, 2014). Curiosity led Christiansen to investigate why errors were being made in operating rooms, but these same errors did not occur when the doctors were under less stress (NEJM, 2014).

Christiansen explained why he believes doctors make mistakes under pressure:

> You can push anyone to a level of pressure where they make cognitive mistakes. We discovered that many of the decision-making mistakes that lead to medical errors are grounded in a lack of knowledge—basic knowledge such as dosages, conversion factors, and so forth. We observed through the simulators that a

> physician's inability to recall trivial information would place them under excessive cognitive workload, leading to errors where, for example, they might fail to ask a colleague for assistance. While we could try to train physicians to become better at asking for help, we also became fascinated with the question of "Why are they under high cognitive workload at all?" We started to look at how we might solve the problem from the other end—by improving learning and making it easier for physicians to recall basic medical knowledge so that they can keep more cognitive capacity available for addressing the really difficult problems. From there, we started doing research into various tutoring systems. By taking study tools rooted exclusively in repetition and adding even simple intelligence, we discovered that we could make them much more effective. Essentially, we found a way to solve a very fundamental problem that affects learning in every field, including complex ones such as medicine. (as cited in NEJM, 2014, p. 1)

Christiansen eventually created a learning tool aimed to lessen the doctor's cognitive load by helping the doctor learn the information he or she was struggling with in the moment of pressure (NEJM, 2014). This learning tool was called LearnSmart (NEJM, 2014).

Advantages of LearnSmart

LearnSmart contains numerous questions or probes that have been created for the objectives the student should know (McGraw-Hill Education, 2015). The questions are presented one-by-one, but before the student answers the question, he or she ranks his or her confidence in answering that question (McGraw-Hill Education, 2015). The confidence scale ranges from *fully confident* to *no confidence*, and depending on whether the student is correct or not, the complex algorithm in LearnSmart produces future questions specifically designed to target areas in which the student is weak (NEJM, 2014). Christiansen explained LearnSmart by comparing it to a carwash:

> Perhaps the best way to comprehend our adaptive learning software is to think of an automated car wash. It is very important for the machines to move close enough to each car to clean effectively without doing any damage. However, it is not very feasible to try to preprogram all the various machines within the car wash to recognize and adapt to every possible make, model, and configuration of car that might pass through. Nor is it particularly feasible to try to make the system remember people's specific cars, because even that will change from time to time. Instead, the car wash uses sensors to decide how tall or wide a vehicle is, whether or not there is a spoiler on the back, and so forth. If the machine encounters a spoiler, it simply moves up and continues on. That is essentially how our algorithms work. They measure where you are at any given time and adapt in the moment—but not all adaptive learning products are engineered to work this way. Many try to rely on having that fixed map of all the makes, models, and configurations or by defining the particular car a person drives. That is not very efficient, especially if you believe, as we do, that people are infinitely different in terms of how they learn. The better you are at being adaptive, the stronger the learning proposition. The more you can shape carefully around each individual, the more precisely you can suggest the best ways for them to move forward in their learning processes. (as cited in NEJM, 2014, p. 2)

The confidence levels associated with each probe create metacognitive data (McGraw-Hill Education, 2015). Metacognitive data are generated from metacognition, which is simply defined as knowing what one knows; one's own personal knowledge variables (Chew, 2014; Logan, Castel, Haber, & Viehman, 2012; Tanner, 2012). If a student is aware that he or she knows certain terms and is uncertain of other terms in a particular course, then the rational action would be for the student to concentrate on the terms that are unknown (Chew, 2014). The problem most students have is they are acutely unaware of what they do not know, thus too much time is spent on studying things they already know, and this creates an inefficient system of studying (Chew, 2014; NEJM, 2014, Tanner, 2012).

Metacognitive data can be used to shed light on the unknowns, which has been shown to be a predictor of intelligence (Wismath, Orr, & Good, 2014). LearnSmart not only predicts a student's knowledge based on accurate or inaccurate answers, it uses metacognitive data to determine the student's cognitive confidence in the answer which helps the program select future questions to ask the student to increase his or her cognitive awareness (McGraw-Hill Education, 2015). The program adapts to the student to offer a personalized experience based on his or her selection on one of four confidence identifiers (McGraw-Hill Education, 2015; NEJM, 2014; Waters, 2014; Webley, 2013) (see Figure 1).

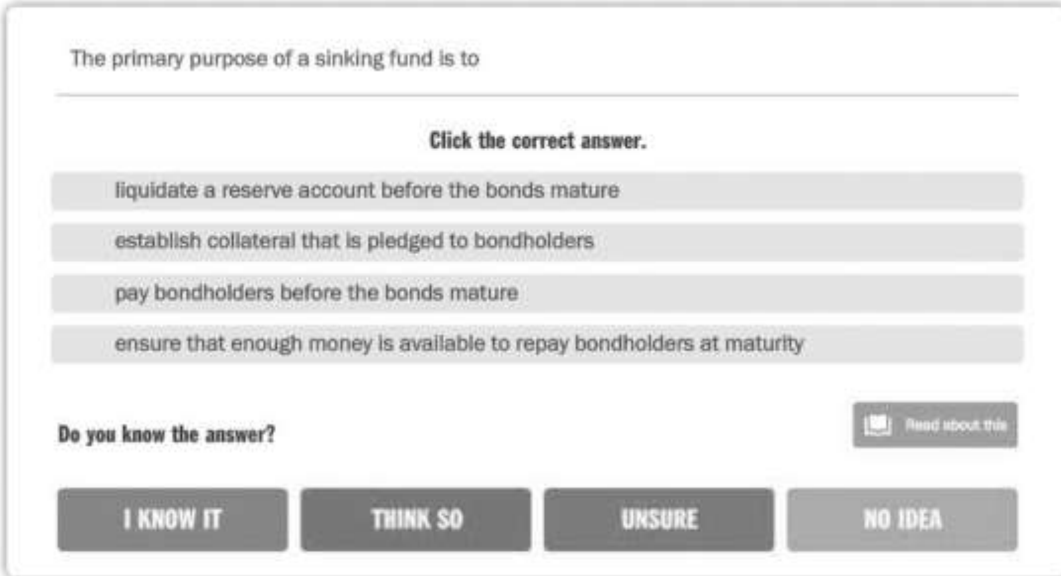

Figure 1. Sample LearnSmart question as it appears on a screen. From *McGraw-Hill LearnSmart Module* (2015) by McGraw-Hill Education. Adapted with permission.

Practices taught within the metacognitive approach to learning include sense-making, self-assessment, and reflection on what worked and what improvement is needed (Chew, 2014; Tanner, 2012). Metacognitive monitoring activities create the basis of what is called adaptive expertise (Baroody & Dowker, 2013). LearnSmart uses several of these metacognitive skill-building exercises in an attempt to increase metacognition (see Figure 2). Students are presented with their scores, the questions they missed the most frequently, their current learning status, self-assessments, and other information that increases the students' own understanding of their current knowledge.

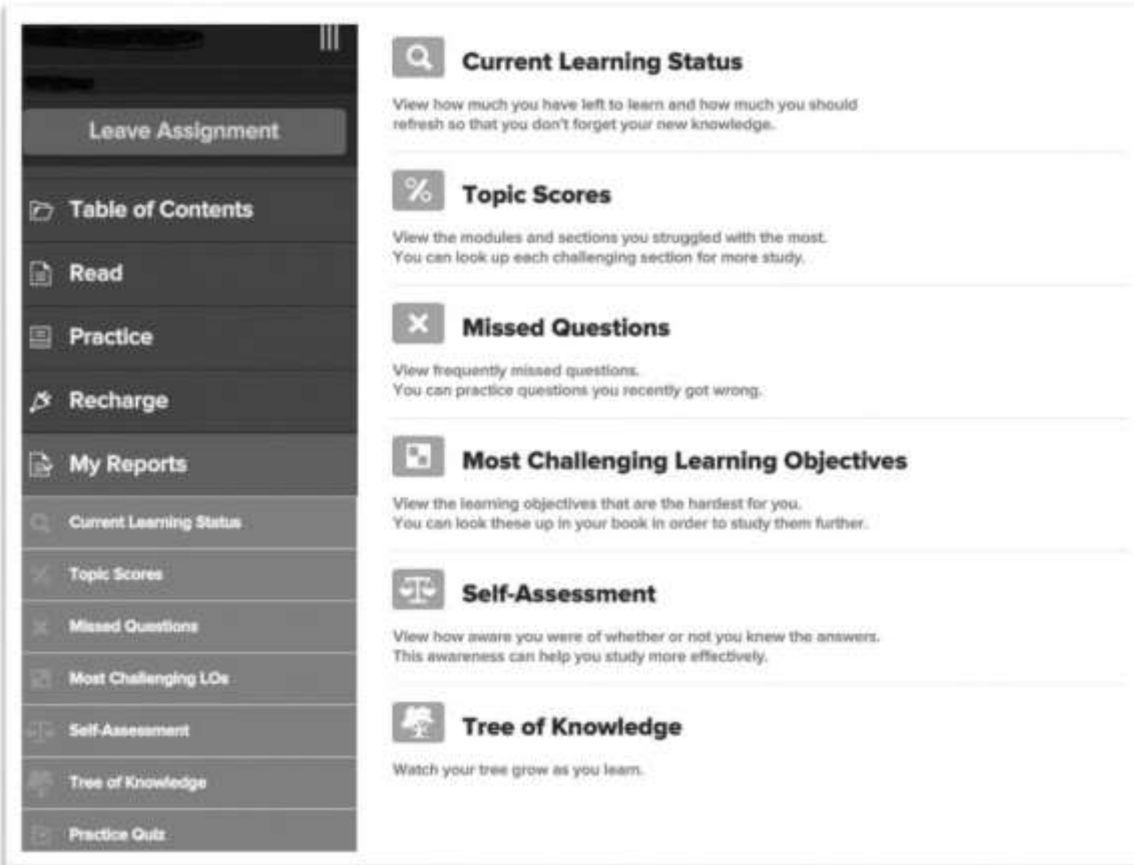

Figure 2. Sample LearnSmart metacognitive skill-building information as it appears on a screen. From *McGraw-Hill LearnSmart Metacognitive Skills Report* (2015) by McGraw-Hill Education. Adapted with permission.

According to White, Collins, and Frederickson (2011), the teaching of metacognitive activities must be incorporated into the subject matter students are learning. Metacognitive strategies are not generic across all subjects, and researchers have shown that attempts to teach metacognitive strategies generically quite often leads to inability to transfer the information into memory (White et al., 2011). LearnSmart provides students with immediate feedback after each question is answered, thereby helping students build their own metacognitive skills (see Figure 3).

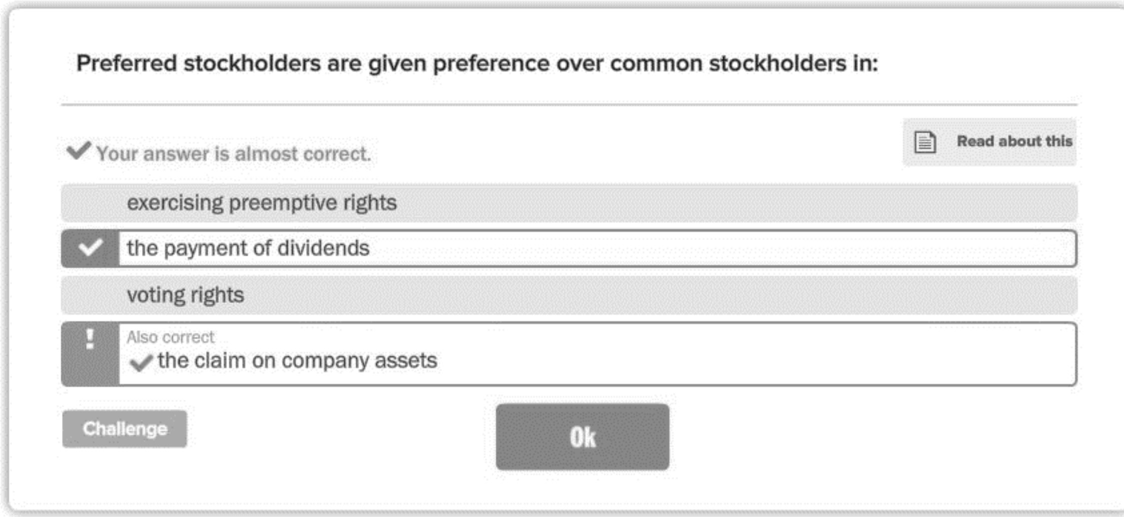

Figure 3. Sample LearnSmart question feedback as it appears on a screen. From *McGraw-Hill LearnSmart Module* (2015) by McGraw-Hill Education. Adapted with permission.

Direct instruction of metacognitive strategies to students in context has been shown to improve understanding in physics (White et al., 2011), written composition (Chew, 2014), heuristic methods for mathematical problem solving, and in the transference of information to new settings and events (Schoenfeld, 2014).

The Results of ALT Studies

The major emphasis of educational institutions should be placed on whether ALT tools produce positive outcomes (Griff & Matter, 2013, Riddell, 2013; Waters, 2014; Zimmer, 2014). Since these tools are still relatively new, the empirical research is limited, but there are several large studies in recent years that should be evaluated (Cooke et al, 2008; Griff & Matter, 2013; James, 2012; McGraw-Hill Education, 2015; Zimmer, 2014). The outcomes of several large studies follow.

Teach to One is an adaptive learning tool used in Brooklyn, NY, at 15 junior high schools from 2013-2015 (Huntsberry, 2015). Students arrive in the morning, check-in with a computer, and then are told which classrooms to go to, the tables at which to sit, the lessons they will learn that day, and what lessons need to come next (Huntsberry, 2015). The lessons range from a variety of courses and are similar in presentation to other ALT platforms (Huntsberry, 2015). The results of the first year's experiment were mixed, but those same students performed 47% higher in the second year of the study (Huntsberry, 2015). According to Reich, a researcher at Harvard who has reviewed the study, 47% did not represent all the students from the first year's data, thus creating confusion about how many students increased their performance in the second year (Reich, 2014).

Students and faculty at Arizona State University took part in a large developmental math study launched in 2010 with ALT-designer, Knewton, in which the program was built and aligned to the Common Core Standards (Waters, 2015). Waters (2015) stated "the system was both facilitator-driven and assessment-driven. It used student data to figure out what students know and how they learn best, and then recommended what concept in the course each student should study next" (p. 2). By 2013, the project was credited with an "18% increase in pass rates and a 47% drop in student withdrawals" (Waters, 2015, p. 2). This positive increase led to a savings of over $12 million for Arizona State University (Zimmer, 2014).

Smaller studies included an ALT study using Smart Sparrow in an engineering course at the University of New South Wales that "led to a 55% decline in drop-out rates" (Zimmer, 2014, p. 1), and a study using LearnSmart in introductory biology classes at

Appalachian State University that showed an increase in overall test scores in students who used LearnSmart modules (James, 2012). McGraw-Hill Education has collective data from 34 different studies that shows an overall increase of 10.8% in passing grades when using LearnSmart as a required piece of the course curriculum (McGraw-Hill Education, 2015). An observational study by Griff and Matter (2013) using LearnSmart in anatomy and physiology courses at six higher-education institutions in the Midwest yielded insignificant results overall, but one segment of the study, involving two community colleges, showed increases in exam scores from students who used LearnSmart voluntarily.

Seven additional studies at six colleges included over 700 anatomy and physiology students who were required to use LearnSmart during the course (McGraw-Hill Education, 2015). The instructors reported their overall increase in pass rates to be 11.5% higher compared to students who were not required to use LearnSmart (McGraw-Hill Education, 2015). Additionally, retention rates increased by 10% in the sections that required students to use LearnSmart (McGraw-Hill Education, 2015). A study of psychology students at New Mexico State University in 2009 resulted in an increase of 10.2% in overall exam scores from students who completed all of the required LearnSmart modules (McGraw-Hill Education, 2015).

Additional non-quantifiable benefits of LearnSmart were also noted in several studies, including increases in student engagement and motivation (McGraw-Hill Education, 2015). In one study in a management class at Siena College, the instructor reported students had higher-levels of engagement in class during the time period that LearnSmart was required (McGraw-Hill Education, 2015). The students also performed better on assessments and class projects (McGraw-Hill Education, 2015). In another study at the University of Cincinnati, the instructor reported students had higher-levels of engagement in class, and the instructor was able to use the LearnSmart metacognitive data to tailor curriculum to the learning objectives that were most commonly missed by students (McGraw-Hill Education, 2015).

Summary

The cuts to higher-education funding since 2009 have been severe for most states, and many have not restored funding to the former levels even today (Mitchell et al., 2014). Administrators and faculty members at institutions of higher-education are looking for ways to reduce spending and increase revenues in order to keep operating budgets balanced, but many administrators are realizing that finding additional streams of revenue is elusive and cutting expenses often leads to a decrease in the quality of the education they are providing (Education Growth Advisors, 2014; Mitchell et al., 2014; Zimmer, 2014). Though impossible years ago due to high costs and ineffectiveness, technology has become less expensive, effective, and readily available (Fletcher, 2013; Huntsberry, 2015; Riddell, 2013; Webley, 2013). The three obstacles: cost, effectiveness, and availability, once called the “Iron Triangle” (Education Growth Advisors, 2014, p. 2), have now become penetrable through the use of ALT tools that personalize learning for each student at a price that is only marginally higher than traditional teaching methods (Waters, 2014). For higher-education institutions, ALT is reshaping the classroom creating improved student performance (Huntsberry, 2015; James, 2012; Zimmer, 2014) and reducing costs (Riddell, 2013; Webley, 2013).

In Chapter Three, the problem and purpose of this study are restated, and there is a review of the research questions and hypotheses that guided data collection and analysis. The majority of Chapter Three provides a comprehensive rationale for and description of the methodology employed in the study. Furthermore, the chapter contains a description of the population and sample studied, data collection methods, and data analysis procedures used in this study.

In Chapter Four, the results from this quantitative study on the impact of using the ALT, LearnSmart, in an introductory business course at higher-education institutions are presented and discussed. There is a review of the problem and purpose of the study as well as a summary of the instrumentation and data collection process. In addition, the findings from each research question are presented and explained.

In Chapter Five, the study is concluded with a summary of the research and data analysis. Recommendations are made for future classroom instructional strategies based on the results of the study. Suggestions for modifications to this study for additional future research are made in order to explore variations of ALT use at higher-education institutions.

Chapter Three: Methodology

The purpose of this study was to demonstrate the impact of adaptive learning technology (ALT) on learning in introductory business courses at higher education institutions. Past researchers indicate the use of ALTs increase learning in mathematics (Waters, 2015), accounting (Phillips & Johnson, 2011), foreign languages (Lee et al., 2011), anatomy and physiology at community colleges (Griff & Matter, 2012), general health discipline studies (Cooke et al., 2008), and biology (James, 2012). In addition, based on 34 smaller anecdotal studies, McGraw-Hill Education researchers found a 10.8% increase in passing grades when using the ALT, LearnSmart, as a required piece of the course curriculum (McGraw-Hill Education, 2015).

In this chapter, the problem addressed in this study is concisely restated. There is a review of the research questions and hypotheses that guided data collection and analysis. The majority of this chapter provides a comprehensive rationale for and description of the methodology employed in the study. Furthermore, this chapter contains a description of the population and sample studied, data collection methods, and data analysis procedures used in this study.

Problem and Purpose Overview

As mentioned in Chapter One, a review of current literature has revealed a lack of empirical studies of ALTs use in business courses. There are many studies and findings that are anecdotal in nature with little or no additional information existing relating to the reliability or validity of the studies (McGraw-Hill Education, 2015). The purpose of this study was to determine if using the ALT, LearnSmart, in seated introductory business courses had an impact on unit exam scores. The study was also created to find any differences between varying time increments used with the ALT and student performance on exam scores. Additionally, general implications of metacognition correlations between a student's confidence in the ALT module and his or her performance on the unit exam were assessed in the study. The findings of this study could be used by teachers of business courses to support the innovation with new pedagogies in course design, and it could be used by higher-education institutions and business departments wishing to assess the use of an ALT in introductory business courses. Furthermore, developers of ALTs could use the findings to inform future innovation of the technologies.

Research questions and hypotheses. The following research questions guided the study:

1. Is there a statistically significant difference in mean exam scores based on the amount of time the ALT, LearnSmart, is used in an introductory business course?

$H1_0$: There is no statistically significant difference between mean exam scores based on the amount of time the ALT, LearnSmart, is used in an introductory business course.

$H1_a$: There is a statistically significant difference between mean exam scores based on the amount of time the ALT, LearnSmart, is used in an introductory business course.

2. Is there a statistically significant correlation between a student's metacognitive confidence in answering questions in LearnSmart modules and his or her unit exam score?

H2_0: There is no statistically significant correlation in the unit exam scores in an introductory business course of students based on metacognitive confidence in answering questions in LearnSmart modules.

H2_a: There is a statistically significant correlation in the unit exam scores in an introductory business course of students based on metacognitive confidence in answering questions in LearnSmart modules.

3. Is there a statistically significant difference in mean exam scores based on having prior experience using LearnSmart?

H3_0: There is no statistically significant difference in mean exam scores based on having prior experience using LearnSmart.

H3_a: There is a statistically significant difference in mean exam scores based on having prior experience using LearnSmart.

Research Design

The purpose of this study was to gain an understanding of a previously unknown area (Creswell, 2013). To do that most effectively, a quasi-experimental design was used. The approach used was quantitative in order to accurately address and answer the questions posed in the study. A quantitative study is effective for analyzing increases and decreases in student learning and providing a numerical range of the magnitude of the changes (Bluman, 2014; Creswell, 2013). A quantitative assessment tool, a unit exam, was used to measure student performance (Creswell, 2013). The results should generalize beyond the limitations imposed by this study (Seltman, 2015). Qualitative measures and findings would not accurately address and answer the research questions posed in the study.

The design of the study involved students enrolled in an introductory business course at three separate community colleges. Three instructors were involved in the study, one at each college. Each instructor randomly assigned one of his or her three sections of the course to receive a treatment. One section served as a control group and was not assigned the LearnSmart modules. The second section was assigned to complete a 20-minute LearnSmart module for each of the two chapters covered before the assessment, and the third section was assigned a 40-minute LearnSmart module for each of the two chapters covered before the assessment. The instructors taught each section uniformly. In order to prevent contamination, whole sections of students were used to form the treatment groups instead of randomly dividing each section of students into three groups (Seltman, 2015). Students were given the option to have their data analyzed in the study, and there was no coercion by the instructor or the researcher to consent to having their data analyzed.

Population and Sample

The population of this study consisted of students in nine sections of introductory business courses at three large community colleges in the Midwest. The study took place during the fall semester of 2015, and the sample consisted of 112 students. The nine specific sections were selected in order to answer the research questions that guided the study. The sample was assumed to be representative of the total population of students taking introductory business courses across the United States at community colleges; thus the study may be considered to be externally valid and generalized, allowing for the application of the results to a broader population (Fraenkel, Wallen, & Hyun, 2011; Seltman, 2015).

The use of the ALT, LearnSmart, was part of the curriculum in the sections that were studied. Therefore, recruitment was limited to asking students to participate in the study. Participants were asked to participate in the study by the instructor of the course in which they were enrolled. Participation was voluntary, and participation in the study did not change the curriculum of the course or the normal pedagogy of the instructor since LearnSmart was already a part of the curriculum in the course and a unit exam was also part of the normal assessment process. Written acceptance on the Informed Consent Form (see Appendix A) was secured by a staff member (SM) of each college and mailed back to the researcher for storage.

One section of students at each institution, group one (G1), did not use LearnSmart before the exam, and the other two sections at each institution did use LearnSmart. Group two (G2) was asked to complete a 20-minute per chapter LearnSmart module for chapters 17 and 18 in the McGraw-Hill textbook, *Understanding Business,* 11th ed., authored by Nickles, McHugh, and McHugh (2015). Group three (G3) was asked to complete a 40-minute per chapter LearnSmart module for chapters 17 and 18. A 30 question multiple-choice and true-false exam (see Appendix B) was given to the students at the end of the unit. The students in G1 were allowed to take an additional exam created by their instructor after the study with the aid of LearnSmart, if requested. Students were asked by their instructor to place an “x” at the top of their exam if they had no experience using LearnSmart before this assignment was given. The exams were graded by the instructors, and the data were collected from the exams by the instructors at the participating institutions. The instructors created a corresponding code for each student. The data were then entered into a Microsoft Excel Spreadsheet and electronically sent to the SM. The SM verified the student's acceptance on the Informed Consent Form and then removed all identifiable data from the spreadsheet. The spreadsheet was then electronically sent to the researcher for analysis. Only data from those participants who signed the consent form were forwarded to the researcher.

The major unit studied is referred to as the analysis unit (Creswell, 2013). The analysis units for research question one and three were the groups of students in the sections under study. The analysis units for research question two were the individual students in the sections under study.

Instrumentation

Instrument rationale. The instrument used for the assessment in this study was a 30 question multiple-choice and true-false exam covering chapters 17 and 18 in the McGraw-Hill textbook, *Understanding Business,* 11th ed., authored by Nickles et al. (2015). Chapters 17 and 18, "Understanding Accounting and Financial Information" and "Financial Management," respectively, are two chapters that commonly make up a unit taught in the introductory business course (Nickles et al., 2015). This study was designed to measure the surface knowledge that is retained and recalled through the assessment of a multiple-choice and true-false exam. Surface knowledge is information held in one's memory for shorter periods of time and is less likely to be internalized into deeper knowledge unless additional instruction is given (Dennehy, 2014). Multiple-choice and true-false question assessments provide a way of measuring information retention (Dennehy, 2014); thus a multiple-choice and true-false assessment provided quantifiable data that were needed to answer the research questions guiding this study (Fraenkel et al., 2011).

Most students will learn information in the way they believe they will be asked to demonstrate it on an assessment; therefore, they prepare accordingly for the expected performance requirements (Dennehy, 2014). Students usually study information in the format in which they expect to see the assessment displayed (Dennehy, 2014). The LearnSmart modules students completed in the experiment were mostly multiple-choice and true-false questions; thus assessing students through the use of multiple-choice and true-false questions corresponds with the form of treatment.

Instrument construction. The 30 question multiple-choice and true-false exam was created by the researcher by developing questions derived from chapters 17 and 18 in the McGraw-Hill textbook, *Understanding Business*, 11th ed., authored by Nickles et al. (2015). The assessment instrument was initially constructed by the researcher, and then the assessment was provided to three subject matter experts to establish content validity. Suggestions and modifications were made when deemed necessary by the experts. The exam was given in-class to the students, and there were no additional study aids available during the exam time.

The collection of metacognitive data was obtained through LearnSmart (McGraw-Hill Education, 2015). LearnSmart reports the percentage of questions-answered by students at certain confidence levels (NEJM, 2014). Based on students selecting one of four confidence levels before answering LearnSmart questions, the program is able to record metacognition (see Figure 4).

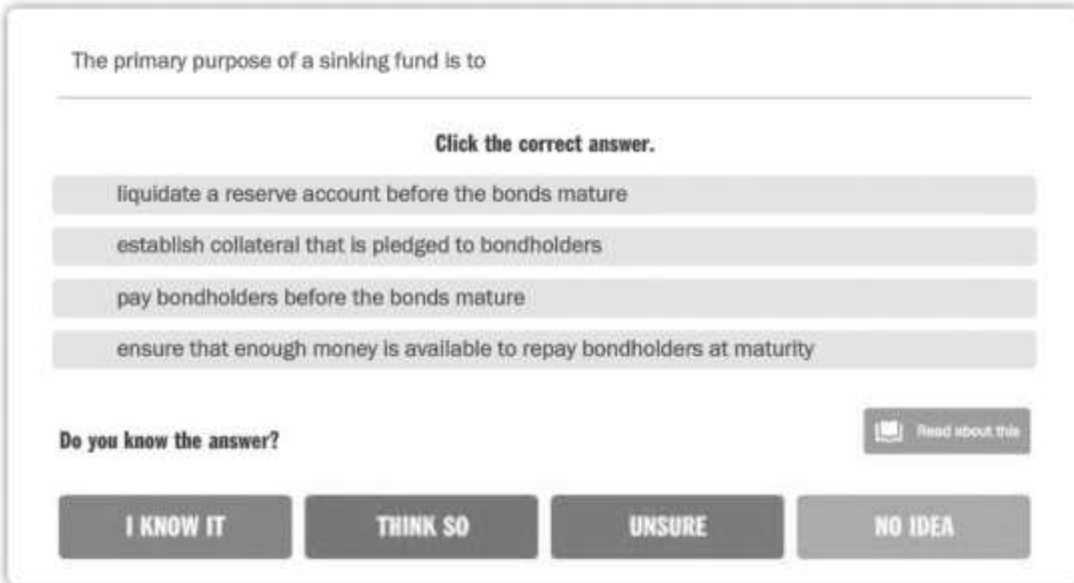

Figure 4. Sample LearnSmart module screen. From *McGraw-Hill LearnSmart Module* (2015) by McGraw-Hill Education. Adapted with permission.

Before answering a question in LearnSmart, students are asked to select a confidence level in answering. The options available to the student include: "I KNOW IT," "THINK SO," "UNSURE," and "NO IDEA" (McGraw-Hill Education, 2015). If a student selects "I KNOW IT" or "THINK SO," and answers the question correctly, then LearnSmart records these metacognitive data into a column titled, "Correct & aware" (McGraw-Hill Education, 2015). If a student selects "UNSURE" or "NO IDEA" and answers the question correctly, then LearnSmart records these metacognitive data into a column titled, "Correct & unaware" (McGraw-Hill Education, 2015). If a student selects "UNSURE" or "NO IDEA" and answers the question incorrectly, then LearnSmart records these metacognitive data into a column titled, "Incorrect & aware" (McGraw-Hill Education, 2015). If a student selects "I KNOW IT" or "THINK SO" and answers the question incorrectly, then LearnSmart records these metacognitive data into a column titled, “Incorrect & unaware*”* (McGraw Hill, 2015) (see Figure 5).

Metacognitive skills LearnSmart

Student	Correct & aware	Correct & unaware	Incorrect & aware	Incorrect & unaware	E-mail
	89%	0%	1%	10%	
	68%	2%	16%	14%	
	72%	3%	8%	17%	
	93%	0%	0%	7%	
	87%	0%	2%	11%	
	74%	1%	5%	20%	
	31%	1%	36%	32%	
	89%	0%	0%	11%	
	64%	1%	7%	28%	
	83%	0%	1%	16%	
	70%	0%	6%	24%	
	92%	0%	0%	8%	
	80%	0%	2%	19%	
	89%	0%	1%	10%	
	90%	1%	2%	8%	
	72%	1%	8%	19%	
	81%	1%	3%	14%	
	75%	1%	8%	16%	
	94%	0%	0%	6%	
	96%	0%	0%	4%	
	75%	0%	2%	23%	

Figure 5. LearnSmart metacognitive skills sample report. From *McGraw-Hill LearnSmart Metacognitive Skills Report* (2015) by McGraw-Hill Education. Adapted with permission.

Instrument reliability and validity: Internal validity was established by obtaining external expert validation that the assessment questions measure the surface knowledge of chapters 17 and 18 in the McGraw-Hill textbook, *Understanding Business*, 11th ed., authored by Nickles et al. (2015). Three subject matter experts examined the assessment instrument in order to establish its validity. Suggestions and modifications to the assessment were made when necessary until consensus was achieved.

Construct validity is a term used to describe how well “the measurement can stand in for the scientific concepts or constructs that are the real targets of scientific learning and inference" (Seltman, 2015, p. 199). Content validity is used to describe the selection of items that will be used on a multi-item survey instrument (Cronbach & Meehl, 1955; Seltman, 2015). In order to select a representative sample of questions from three chapters of material, subject matter experts were used to determine content validity. Cronbach and Meehl (1955) stated in their paper, "Construct Validity in Psychological Tests," there is "no single measure of construct validity, because it is a complex, often judgment-laden set of criteria" (p. 3). Because no confirmed standard of measurement exists to measure learning in an introductory business course, the target of construct validity is difficult to pinpoint; thus content validity was sought in this study (Seltman, 2015).

Power refers to the probability the research will "correctly conclude that the treatment caused a change in the outcome" (Seltman, 2015, p. 205). A type II error (β) would be the opposite of power, a probability that an incorrect conclusion will be made about the variables that caused the outcome; thus power can be presented as $1-\beta$ (Navidi & Monk, 2014; Seltman, 2015). Experiments that have higher power are considered to be more valid, so increasing power is a goal (Seltman, 2015). Increasing the size of the sample is an effective way to increase power as is "increasing the treatment strength in the study" (Seltman, 2015, p. 206). The reliability of the study will be supported through future research on ALTs in business courses.

Data Collection

Once the Institutional Review Board (IRB) approval was obtained from Lindenwood University and the three colleges conducting the experiment (see Appendix C), data collection began. The study consisted of students in three seated introductory business courses taught by the same instructor at each of the three large community colleges in the Midwest. The instructors at each institution administered the exams and collected the exams once complete. There were no additional study aids available to the students, and incomplete exams were removed from the total. Students were asked to place an “x” at the top of the exam if they had no prior experience using LearnSmart.

The instructors created a corresponding code for each student. The exams were scored by the instructor, and then the results from the exams and the LearnSmart modules were entered into a Microsoft Excel spreadsheet given to the SM. The SM verified the signatures on the Informed Consent Form, deleted any identifiable information, and then the spreadsheet was electronically sent to the researcher for analysis. Exams from students in G2 and G3 were checked by the researcher by verifying the completion of the LearnSmart modules to ensure the corresponding students did complete the module. The exams of students who did not complete the modules were removed from the analysis.

Data Analysis

At the conclusion of data collection, raw data from the scored exams and LearnSmart were transferred into a Microsoft Excel spreadsheet by the instructors. A corresponding number code was created by the instructor for each student. The spreadsheet was sent to the SM for Informed Consent Form signature verification, names were deleted from the spreadsheet, and the spreadsheet was sent to the researcher.

The analysis of the data took place next. In order to answer the first research question, a one-way ANOVA was used to find differences among the means of the groups (Bluman, 2014; Navidi & Monk, 2014)). The means of G1, G2, and G3 were compared to each other. An alpha (α) of .05 was set as a limit of how often false results would be accepted (Seltman, 2015). The probability value (p) is the probability of having the mean indicate the alternative hypothesis is true when the null hypothesis is actually true (Bluman, 2014). By using SPSS software, a p value was obtained. If the calculated p value was less than .05, then $H1_0$ was rejected and $H1_a$ was supported by the researcher (Bluman, 2014). If a statistically significant difference was found between the mean exam scores of the groups, post-hoc tests were conducted to determine statistical significant differences between the groups (Seltman, 2015). A Tukey HSD test was conducted with an α set to .05 to determine differences between the groups (Seltman, 2015).

In order to answer the second research question, data pertaining to the student's metacognition were compared to the student's exam score. Using the Data Analysis Add-In in Microsoft Excel, the correlation coefficient (r) was calculated to determine the strength of the relationship between the student's metacognitive score and his or her exam score (Navidi & Monk, 2014). The student's metacognitive score and his or her exam score were then tested for statistical significance using the Pearson Product Moment Correlation (Bluman, 2014). With an α set to .05 as a limit of how often false results would be accepted and the degrees of freedom (df) set at N-2, a t distribution was used to determine the t-value. The r critical (r_{crit}) value was calculated for the t-value in Microsoft Excel. If the r was greater than r_{crit}, then $H2_0$ was rejected and $H2_a$ was supported by the researcher (Bluman, 2014).

In order to answer the third research question, data pertaining to the impact on exam scores based on previous experience using LearnSmart, a two-tailed t-test was performed. The mean exam scores of those students who had previous experience using

LearnSmart in other courses were compared to the mean exam scores of students who had no previous experience using LearnSmart in other courses. By using the Data Analysis Add-In in Microsoft Excel, the two-tailed *t*-test was performed and a *p* value was obtained. An α of .05 was set as a limit of how often false results would be accepted (Seltman, 2015). If the calculated *p* value was less than 0.05, then $H3_0$ was rejected and $H3_a$ was supported by the researcher (Bluman, 2014).

Summary

This quantitative study was created in an attempt to determine if using the ALT, LearnSmart, in seated introductory business courses had an impact on unit exam scores. The study was guided by three research questions aimed at determining whether differences in exam scores were noticed with the use of the ALT, if metacognition while using the ALT correlated to performance, and if previous use of the ALT had an impact on exam performance. Data were obtained from an exam score from nine seated introductory business course sections at three different colleges in the Midwest. Data analysis consisted of a one-way ANOVA between the mean exam scores of each group, a test to determine the correlation coefficient significance in metacognitive scores and exam scores, and a two-tailed *t*-test between the mean exam scores of students who had previous experience using LearnSmart and those who did not.

The guidelines of this study adhered to Lindenwood University's IRB policies. The validity of this study was established based on input from the researcher and three other subject matter experts. The reliability of the study itself will be determined by future research on ALTs in business courses. In Chapter Four, the results from this quantitative study on the impact of using the ALT, LearnSmart, in an introductory business course at higher-education institutions are presented and discussed. There is a review of the problem and purpose of the study as well as a summary of the instrumentation and data collection process. In addition, the findings from each research question are presented and explained.

In Chapter Five, the study is concluded with a summary of the research and data analysis. Recommendations are made for future classroom instructional strategies based on the results of the study. Suggestions for modifications to this study for additional future research are made in order to explore variations of ALT use at higher-education institutions.

Chapter Four: Analysis of Data

Adaptive learning technologies have increased in number, use, and effectiveness in the last two decades (Fletcher, 2013; Huntsberry, 2015; McGraw-Hill Education, 2015; Riddell, 2013; Webley, 2013). As new ALTs emerge, instructors at educational institutions have adopted the use of them, and studies have been conducted revealing positive impacts (Cooke et al., 2008; Fletcher, 2013; Griff & Matter, 2012; James, 2012; Lee et al., 2011; McGraw-Hill Education, 2015; Phillips & Johnson, 2011; Waters, 2014). In this chapter, the results from this quantitative study on the impact of using the ALT, LearnSmart, in an introductory business course at higher-education institutions are presented and discussed.

Problem and Purpose Overview

As previously discussed in Chapter One, a review of current literature in 2015, revealed a shortage of empirical studies in which researchers analyzed the impact of using an ALT in business courses. Although anecdotal studies exist, there is little known about the validity and reliability of the studies (McGraw-Hill Education, 2015). The purpose of this study was to determine if using the ALT, LearnSmart, in seated introductory business courses had an impact on unit exam scores. Secondly, the mean exam scores of the students were analyzed based on time increments related to use of the ALT. In addition, the possible correlations between the students' metacognition in the ALT module and his or her performance on the unit exam were examined. The findings of this study could be used by teachers of business courses to create new instructional methods used in the course, and the findings could be used by leaders at higher-education institutions to assess the effectiveness of an ALT used under these circumstances in introductory business courses. Lastly, ALT developers could use the findings to bring about future innovation of the technologies.

Summary of Instrumentation and Data Collection

The instrument used for the assessment in this study was a 30 question, multiple-choice and true-false exam covering chapters 17 and 18 in the McGraw-Hill textbook, *Understanding Business*, 11th ed., authored by Nickles et al. (2015). This text was used by the three colleges in the study. Chapters 17 and 18, "Understanding Accounting and Financial Information" and "Financial Management," respectively, usually make up a unit taught in the introductory business course (Nickles et al., 2015). This study was designed to measure the surface knowledge that is retained and recalled through the assessment of a multiple-choice and true-false exam. The researcher created the exam from material in chapters 17 and 18, and the process of establishing its validity occurred by having the exam reviewed by three subject matter experts (Chronbach & Meehl, 1955; Navidi & Monk, 2014; Seltman, 2015). Suggestions and modifications were made, when deemed necessary by the experts, until consensus was achieved.

Metacognitive data were collected by LearnSmart. LearnSmart reported the percentage of questions that are answered by students at certain confidence levels (NEJM, 2014). Confidence levels were presented to the student before he or she answered the question (McGraw-Hill Education, 2015). Based on students selecting one of four confidence levels before answering LearnSmart questions, the program recorded metacognition (McGraw-Hill Education, 2015).

Once Institutional Review Board (IRB) approval was obtained from Lindenwood University and the three colleges conducting the experiment, data collection began. The population of the study consisted of students in three seated introductory business courses taught by the same instructors at each of the three large community colleges in the Midwest. The instructors at each institution assigned the LearnSmart modules, administered the exams, and collected the exams once complete. No additional study aids were available to the students during testing, and incomplete exams were removed from the sample. The exams were scored, and then the instructors entered the results into a Microsoft Excel spreadsheet given to the SM. The SM verified the signatures on the Informed Consent Form, deleted any identifiable information, and then the spreadsheet was electronically sent to the researcher for analysis. Exams from students in group two (G2) and group three (G3) were checked by the instructors and the researcher by verifying the completion of the LearnSmart modules to ensure the corresponding students completed the modules. The exams of students who did not complete the modules were removed from the sample and subsequent analysis.

Respondent Demographics

The population of the study included nine sections of an introductory business course at three large community colleges in the Midwest. The participants invited to be part of the study were males and females, 18 to 64 years of age who were enrolled in the sections under study. The initial sampling frame included 164 students. Twelve students did not sign the Informed Consent Form, 40 students signed the Informed Consent Form but did not complete the assignment, which brought the final sample size to 112 students.

Reliability and Validity of Results

Construct validity is a term used to describe the ability of a measurement to replace, or stand in for, the scientific concepts and constructs in order to make inference to those of the actual targets of the study (Cronbach & Meehl, 1955; Seltman, 2015). Cronbach and Meehl (1955) stated in their paper, "Construct Validity in Psychological Tests," there is "not a single way to measure construct validity" due to an overwhelming set of variables (p. 282). Because of the variables involved in establishing construct validity of an assessment covering two chapters in an introductory business course, a definitive measurement of learning does not exist. Three subject matter experts were used to refine the representative sample of questions constructed by the researcher from the two chapters of material used in the study in order to establish content validity (Creswell 2013; Cronbach & Meehl, 1955; Seltman, 2015). Modifications were made until the subject matter experts satisfactorily established content validity (Cronbach & Meehl, 1955; Creswell, 2013).

Power refers to the probability the research will accurately determine if changes to the independent variables caused the change in the dependent variables (Seltman, 2015). A type II error (β) would be the exact opposite situation, a probability that an incorrect conclusion will be made about the variables that caused the outcome, thus power can be presented as $1-\beta$ (Seltman, 2015). Increasing the power of an experiment is a goal, because experiments that have higher power are considered to be more valid (Seltman, 2015). Increasing the size of the sample is an effective way to increase power as is "increasing the treatment strength in the study" (Seltman, 2015, p. 206). This study involved three colleges and a large sample size; thus this study should have high power (Seltman, 2015). Future research on ALTs in business courses will help support the reliability and validity of this study (Creswell, 2013; Seltman, 2015).

Data Analysis

The protocol for analyzing and protecting the data was in accordance with the Lindenwood University IRB policy. Before the data were sent to the researcher to be analyzed, the instructors created and assigned a corresponding code for each student. The instructors keyed the exam scores and the LearnSmart metacognitive data into a Microsoft Excel spreadsheet. The spreadsheet was sent to the SM to verify the Informed Consent Form signatures. The SM removed the names from the spreadsheet, and then the SM electronically sent the spreadsheet to the researcher.

The researcher opened the spreadsheet and organized the data into columns for analysis. Three columns were made for research question one. The first column contained the exam scores of G1 for all three colleges. The second column contained the exams scores of G2 for all three colleges, and the third column contained the exam scores of G3 for all three colleges. The data from the three columns was then electronically copied and pasted into the statistical analysis program, SPSS, in order to conduct a one-way ANOVA.

The researcher then electronically copied the exam scores from G2 and G3 into a column. The metacognitive data in the spreadsheet from G2 and G3 were electronically copied and pasted into two columns next to the column that contained the exam scores. The first column of data contained the total metacognitive scores of “Correct & aware” and “Incorrect & aware.” The second column of data contained the metacognitive scores of “Correct & aware.” The columns of data were used to conduct a Pearson Product Moment Correlation test to find correlation.

The researcher then electronically copied the exam scores from those in G2 and G3 that were indicated as not having prior experience using LearnSmart and pasted those into a separate column. The exam scores of students who had used LearnSmart before were electronically copied and pasted into a column. The data in the two columns were used to conduct a two-tailed *t*-test.

Findings from research question 1. The first research question *(Is there a statistically significant difference in mean exam scores based on the amount of time the ALT, LearnSmart, is used in an introductory business course?)* was analyzed by conducting a one-way ANOVA on the exam scores. A one-way, between-subjects ANOVA is the appropriate statistical test to conduct to find equality of more than two means for a single quantitative outcome variable (Bluman, 2015; Navidi & Monk, 2014; Seltman, 2015). The mean for G1 was 20.7, the mean for G2 was 20.5, and the mean for G3 was 23.4. The one-way ANOVA resulted in $F(2, 109) = 4.28$, $p = .016$, with α set at .05, a significance value (p) of .016 was reported between G1, G2, and G3. With an F statistic, 4.28, greater than the F_{crit} statistic, 3.08, the null hypothesis was rejected, and it was concluded there was a statistically significant difference in exam scores between the three groups (see Table 1).

Table 1

Summary of One-Way ANOVA Data

Group	Count	*M*	Variance
1	70	20.73	20.64
2	14	20.5	18.88
3	28	23.43	12.77

ANOVA

Source of Variation	*SS*	*df*	*M*	*F*	*P*	*F crit*
Between Groups	158.05	2	79.03	4.28	.016	3.08
Within Groups	2014.2	109	18.48			
Total	2172.25	111				

Note. *N* = 112, *M* = mean score, *df* = degrees of freedom, *p* = significance value, *F* = F statistic, *F crit* = F critical value.

An additional post hoc Tukey HSD test revealed a significance value of .016, a statistically significant difference between G1 and G3, requiring $H1_0$ to be rejected and $H1_a$ to be supported (Seltman, 2015). This indicated there was a statistically significant positive difference in exam scores between those students who did not use LearnSmart and those students who completed a 40-minute LearnSmart module before the exam.

In addition to statistical significance, there is practical significance in analyzing the mean exam scores (Navidi & Monk, 2014; Seltman, 2015). The mean exam score of G1 was 20.7, G2 was 20.5, and the mean exam score of G3 was 23.4 (see Table 2). Students who completed a 20-minute LearnSmart module scored 1.1 % lower on the exam compared to those who did not use LearnSmart. Students who completed a 40-minute LearnSmart module showed an increase of 13% in exam scores versus those who did not use LearnSmart.

Table 2

Summary of Mean Exam Score Differences

Group	Count	*M*	Percent increase/decrease from G1
G1	70	20.73	-
G2	14	20.5	-1.10%
G3	28	23.43	13.03%

Note. N = 112. M = mean exam score.

Findings from research question 2. The second research question *(Is there a statistically significant correlation between a student's metacognitive confidence in answering questions in LearnSmart modules and his or her unit exam score?)* was analyzed by finding the Pearson Product Moment Correlation coefficient (r) between each student's LearnSmart metacognitive scores in the categories of "Correct & aware," and "Incorrect and aware" and his or her exam scores. Statistical significance was analyzed at α set at .05.

A positive trend line (see Figure 6), correlation statistic of .407, and a significance value, p, of .042 resulted when analyzed. The r_{crit} value was .304, less than r, thus this correlation was moderately strong and was statistically significant (Bluman, 2015; Navidi & Monk, 2014; Seltman, 2015). Since r was greater than r_{crit}, $H2_0$ was rejected and $H2_a$ was supported, which indicated metacognition in answering LearnSmart module questions did have a significant positive relationship to exam scores.

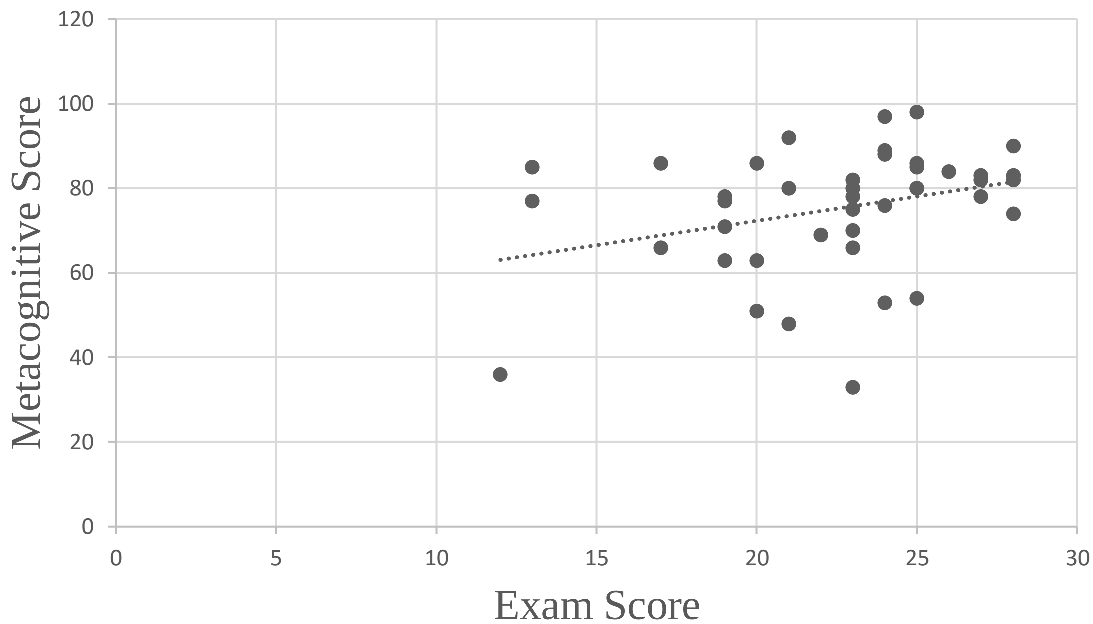

Figure 6. Scatterplot of metacognitive score by exam score. Solid dots represent individual student data. The dashed line represents the trend line of the data for the equation y =1.2x + 52.557.

Findings from research question 3. The third research question *(Is there a statistically significant difference in mean exam scores based on having prior experience using LearnSmart?)* was analyzed by conducting a statistical two-tailed *t*-test between the exam scores of those students who had prior experience using LearnSmart and those who did not in G2 and G3. There were 21 students who had prior experience using LearnSmart before this study, and there were 21 students who did not. The mean score for those with prior LearnSmart experience was 21.3 (M = 21.3, SD = 3.9), while the mean score for those with no LearnSmart experience was 23.6 (M = 23.6, SD = 3.9). The result was a decrease of 9.88 % in the mean exam score of those who used LearnSmart previous to the study. The differences between exam scores of these two groups were not statistically significant with $t(40) = 2.02$, $p = .061$, with α set at .05, the $H3_0$ null hypothesis was not rejected (see Table 3). Furthermore, it might be anticipated students with prior experience would score higher on the exam, but in this situation they did worse than students with no prior experience using LearnSmart.

Table 3

Summary of Analysis for Research Question 3

	Previous Experience with LearnSmart	No Experience with LearnSmart
M	21.29	23.62
Variance	15.31	15.35
Count	21	21

Note. $N = 42$, $\alpha = .05$, $p = .061$.

The mean exam score of students who had prior experience using LearnSmart was 21.3 versus a mean exam score of 23.6 of students who did not have prior experience using LearnSmart. Since the p value was greater than α, $H3_0$ was not rejected resulting in the fact there was no statistically significant difference in mean exam scores of students who had prior experience using LearnSmart versus students who did not have prior experience using LearnSmart.

Summary

From the data collected and analyzed in this study, there was a statistically significant increase in exam scores of students in an introductory business course who completed the 40-minute LearnSmart modules prior to the exam compared to students who did not use LearnSmart. There was also a statistically significant correlation between a student's metacognitive score and his or her exam score. The analysis of exam scores of students who had prior LearnSmart experience resulted in lower exam scores compared to students who had no prior experience using LearnSmart, though the difference was not statistically significant.

In Chapter Five, the study is concluded with a summary of the research and data analysis. Recommendations are made for future classroom instructional strategies based on the results of the study. Suggestions for modifications to this study for additional future research are made in order to explore variations of ALT use at higher-education institutions.

Chapter Five: Summary and Conclusions

In this chapter the major elements of the study are reviewed. A summary of the findings explained in Chapter Four are discussed. Conclusions and implications supported by current literature are detailed in the section that follows. The end of the chapter is reserved for recommendations and suggestions provided by the researcher. Additionally, areas of future research based upon this study are presented.

Review of the Study

Through the advancements in technology in the last several decades, adaptive learning technologies (ALT) have increased in size, scope, and effectiveness in classrooms across the country (Fletcher, 2013; Huntsberry, 2015; McGraw-Hill Education, 2015; Riddell, 2013; Webley, 2013). Many educators and administrators of schools have sought to add ALTs and other technologies to the classroom, but there has been a relatively small amount of empirical data offered in order to analyze the effectiveness of learning taking place through these additions (Bain & Weston, 2012).

The use of an ALT in traditional learning environments has proven effective in a variety of disciplines in the last two decades (Cooke et al., 2008; Fletcher, 2013; Griff & Matter, 2012; James, 2012; Lee et al., 2011; McGraw-Hill Education, 2015; Phillips & Johnson, 2011; Waters, 2014). Data from earlier studies have caused researchers to take note of the phenomenon in which students perform statistically significantly better when instructed in a one-on-one learning environment compared to learning in a traditional, whole-group environment (Bloom, 1984; Horn, 2012; Tight, 2012; Johnson, 2011).

Some researchers have offered a rationale that learning through a one-on-one, adaptive model would be successful due to its ability to allow the instructor to focus his or her attention on one student; therefore, the instructor can adapt quickly to correct an incorrect performance by the student (Bloom, 1984; Tight, 2012). This constructive style of instruction builds directly upon long-standing learning theories (Isaacs, 2015; Müller et al., 2015; Piaget, 1972); thus, ALTs could have the ability to play a part in more effective learning strategies (Dietvorst et al., 2014; Dornisch, 2013; Education Growth Advisors, 2014; Fletcher, 2014; Horn 2012; Huntsberry, 2015; McGraw-Hill Education, 2015; Riddle, 2013; Waters, 2014; Webley 2013; Zimmer, 2014).

This purpose of this study was to find answers to three questions pertaining to the use of the ALT, LearnSmart, in an introductory business course. The first question, *(Is there a statistically significant difference in mean exam scores based on the amount of time the ALT, LearnSmart, is used in an introductory business course?)*, centered around the basic question of whether the ALT could increase exam score performance when used as a preparatory assignment prior to the exam. The purpose of the first research question was also designed to probe the general understanding of whether varying time increments of the ALT had an impact on performance.

The second question, *(Is there a statistically significant correlation between a student's metacognitive confidence in answering questions in LearnSmart modules and his or her unit exam score?)*, identified the use of a student's general metacognitive ability in answering LearnSmart questions and his or her performance on the exam. The primary focus on this question was to find if a correlation existed between students who had the ability to confidently identify their own current level of knowledge of the subject matter in the preparatory assignment and their score on the exam.

The third and last question posed in this study, *(Is there a statistically significant difference in mean exam scores based on having prior experience using LearnSmart?)*, was designed to address the understanding of a student's prior experience in using the ALT and his or her performance on the exam in order to better understand if there is a connection between the amount of time involved in learning to use the ALT itself and exam performance. Through the data captured from students who had no prior experience using the ALT, the researcher sought to understand how students performed when asked to learn to use the ALT for the first time compared to students who did not have to put forth the cognitive energy to learn this new program.

In order to answer the questions posed in this study, a quantitative study was required to effectively capture and analyze the information needed (Bluman, 2014; Creswell, 2013; Navidi & Monk, 2014; Seltman, 2015). A quantitative study is effective at measuring increases and decreases in student learning and provides a numerical range of the magnitude of the changes (Bluman, 2014; Creswell, 2013); thus, a quantitative assessment tool, a unit exam, was used (Creswell, 2013). The results are generalizable beyond the limitations imposed by this study (Seltman, 2015).

The study took place in nine sections of an introductory business course at three large community colleges in the Midwest in the fall semester of 2015. The recruitment process was limited to asking students who were currently enrolled in the course to participate in the study. Participants were asked to participate in the study by the instructor of the course in which they were enrolled. Participation was voluntary, and participation in the study did not change the curriculum of the course or the normal pedagogy of the instructor since LearnSmart was already included in the course and a unit exam was also part of the normal course assessment process. Written acceptance on the Informed Consent Form was secured from participants by the staff member (SM) and mailed back to the researcher for storage.

One section of students at each institution, group one (G1), did not use LearnSmart before the exam, and the other two sections at each institution did use LearnSmart. Group two (G2) was asked to complete a 20-minute per chapter LearnSmart module for chapters 17 and 18. Group three (G3) was asked to complete a 40-minute per chapter LearnSmart module for chapters 17 and 18. Chapters 17 and 18, "Understanding Accounting and Financial Information" and "Financial Management," respectively, are two chapters commonly taught together to make up a unit in an introductory business course (Nickles et al., 2015).

This study was designed to measure the surface knowledge that is retained and recalled by students through the assessment of a multiple-choice and true-false exam. Surface knowledge is information that is held in one's memory for shorter periods of time and is less likely to be internalized into deeper knowledge unless additional instruction is given (Dennehy, 2014). Multiple-choice and true-false question assessments provide a way of measuring information retention (Dennehy, 2014); thus a multiple-choice and true-false assessment provided quantifiable data needed to answer the research questions guiding this study (Fraenkel et al., 2011).

A 30 question multiple-choice and true-false exam was given to the students at the end of the unit. The students in G1 were allowed to take an additional exam created by their instructor after the study with the aid of LearnSmart, if requested. Students were asked by their instructor to place an "x" at the top of their exams if they had no experience using LearnSmart before this assignment was given. The data were collected from the exams by the instructors at the participating institutions. The instructors created a corresponding code for each student to ensure the privacy of the participants. The data from the exam and LearnSmart modules were then entered into a Microsoft Excel Spreadsheet and electronically sent to the SM. The SM verified the completion of the Informed Consent Form, deleted the names of the students, and then electronically sent the spreadsheet to the researcher for analysis. Only data from those participants who signed the Informed Consent Form were forwarded to the researcher for analysis.

Findings

The first research question, *(Is there a statistically significant difference in mean exam scores based on the amount of time the ALT, LearnSmart, is used in an introductory business course*?*)*, was investigated by conducting a one-way, between-subjects ANOVA of the exam score data from G1, G2, and G3. With α set at .05, the analysis yielded a *p* value of .016, indicating a statistically significant positive difference existed between the groups (Seltman, 2015). An additional post hoc Tukey HSD reported a statistically significant difference existed between G1, the students who did not use LearnSmart, and G3, the students who completed the 40-minute LearnSmart modules. The mean exam score of G1 was 20.7, and the mean exam score of G3 was 23.4, resulting in a 13 % increase in exam scores of students who completed the 40-minute LearnSmart modules compared to students who did not use LearnSmart. The null hypothesis $H1_0$ was rejected and $H1_a$ was supported.

The second research question, *(Is there a statistically significant correlation between a student's metacognitive confidence in answering questions in LearnSmart* *modules and his or her unit exam score?),* was investigated by a Pearson Product Moment Correlation analysis to find a statistically significant correlation between student metacognitive scores and exam scores. The analysis yielded an r of 0.407, an r_{crit} value of .304 at an α set at .05, and the p value was .042, thus determining the correlation that existed to be statistically significant (Seltman, 2015). The null hypothesis $H2_0$ was rejected and $H2_a$ was supported. There was a moderately-strong, statistically significant correlation between higher student metacognitive scores and exam performance (Bluman, 2014; Navidi & Monk, 2014; Fraenkel et al., 2011; Seltman, 2015).

The third research question, *(Is there a statistically significant difference in mean exam scores based on having prior experience using LearnSmart?),* was investigated by conducting a two-tailed t-test between the exam scores of the students in G2 and G3 who had prior experience using LearnSmart and the exam scores of the students in G2 and G3 who did not have prior experience using LearnSmart. There were 21 students who had prior experience using LearnSmart, and the mean exam score of that group was 21.3. There were 21 students who had no prior experience using LearnSmart, and the mean exam score of that group was 23.6. When analyzed with an α set at .05, the two-tailed t-test resulted in a p value of .061, suggesting no statistically significant difference between the two groups (Navidi & Monk, 2014; Seltman, 2015). The null hypothesis $H3_0$ was not rejected.

Conclusions

As discussed in Chapter Three, results from this quantitative study are deemed to be valid due to the design of the study and the instrument assessing the outcomes (Creswell, 2013; Fraenkel et al., 2011; Seltman, 2015). The conclusions drawn in this study are associations based directly to the variables under study (Creswell, 2013; Fraenkel et al., 2011, Seltman, 2015). The data from the study produced meaningful results researchers and instructors at higher-education institutions may find of value in the future when selecting and creating instructional strategies.

The information produced from research question one indicated students perform better on exams when required to complete a longer, 40-minute, LearnSmart module compared to a shorter, 20-minute, LearnSmart module or not using LearnSmart at all. The mean exam score increase was 13% for the group completing the 40-minute LearnSmart modules. This increase was much higher than the researcher expected. It was also surprising to find students who completed the 20-minute LearnSmart modules performed 1.1% lower on the exam compared to students who did not use LearnSmart. This decrease might be caused by the assignment not being long enough to fully engage the students in the material or the ALT not being able to accurately assess the knowledge the student has of the subject matter given the fewer number of questions answered.

After concluding the basic analysis for this study, further analyses were conducted comparing the mean exam scores at each of the three colleges to each other. Two colleges had overall mean exam scores from all groups that were very similar, 22.8 and 23.1, while one college had a mean score of 17.9. In the study it was assumed the students and instructors at each institution would be similar, but the difference in the mean exam scores at one institution indicated a possible difference between the students or instructors at that institution compared to the other two institutions. When the data were analyzed after removing the scores of the lower-performing college, there were no statistically significant differences found between the groups. With an α set at .05, the *p* value was .105.

When each college was analyzed independent of the others, the intra-college two-tailed *t*-test findings of student performance of the two groups of students who used LearnSmart versus the group of students who did not use LearnSmart were noteworthy (see Table 4). The first college had a mean exam score of 22.2 for students who did not use LearnSmart compared to a mean exam score of 24.6 for students who did use LearnSmart. With α set at .05, and a *p* value of .0359, this represents a statistically significant increase of 10.64 % after using LearnSmart. The second college had a mean exam score of 15.8 for students who did not use LearnSmart compared to a mean exam score of 19.3 for students who did use LearnSmart. With an α set at .05, and a *p* value of .007, this represented a statistically significant increase of 22.53 % after using LearnSmart. The third college had a mean exam score of 22.8 for students who did not use LearnSmart compared to a mean exam score of 23.6 for students who did use LearnSmart. With an α set at .05, and a *p* value of .478, this represented an increase of 3.79 % after using LearnSmart. An increase in exam scores of those that used the ALT was noticed in all three colleges.

Table 4

Summary of Data Analysis for Each Individual College

College	No LS Group Mean	LS Group Mean	*t*-test *p*	Increase with LS
1	22.2	22.56	.036	10.64%
2	15.78	19.33	.007	22.53%
3	22.77	23.64	.478	3.79%

Note. a=.05, No LS Mean = mean score of students who did not use LearnSmart, LS Mean = mean score of students who did use LearnSmart, *t*-test *p* = significance value, Increase with LS = percent increase between LS Mean and No LS Mean.

The information produced from research question two indicated student metacognition plays a positive role in learning. The metacognitive score from the LearnSmart metacognitive categories "Correct and aware," and "Incorrect and aware" were analyzed. Statistical significance was analyzed at α of .05. A positive trend line (see Figure 4), correlation statistic of .407, and a significance value, *p*, of .042 resulted when analyzed. The r_{crit} value was .304, less than *r*, thus this correlation was moderately strong, and the correlation was statistically significant (Bluman, 2015; Navidi & Monk, 2014; Seltman, 2015). Data from earlier research support the argument students perform better when students understand what they know and do not know about the subject matter (Chew, 2014). The research from this study adds to the support of the argument. There was a moderately-strong correlation between metacognitive scores in answering LearnSmart questions and exam performance of students who had an awareness they knew the answer or an awareness they did not know the answer (Bluman, 2014; Fraenkel et al., 2011).

Another way of investigating the correlation of metacognitive data involved the analysis of the metacognitive scores in the category of "Correct and aware," which only is calculated when the students are aware they know the answer and they are correct in answering the question. Statistical significance was analyzed at α of .05. A positive trend line and correlation statistic of .315 was observed and indicated a moderately strong correlation between metacognitive scores and exam scores (Bluman, 2015; Navidi & Monk, 2014; Seltman, 2015) (see Figure 7). The r_{crit} value was .214, less than r; thus, this correlation was moderately strong, and the correlation was statistically significant (Bluman, 2015; Navidi & Monk, 2014; Seltman, 2015).

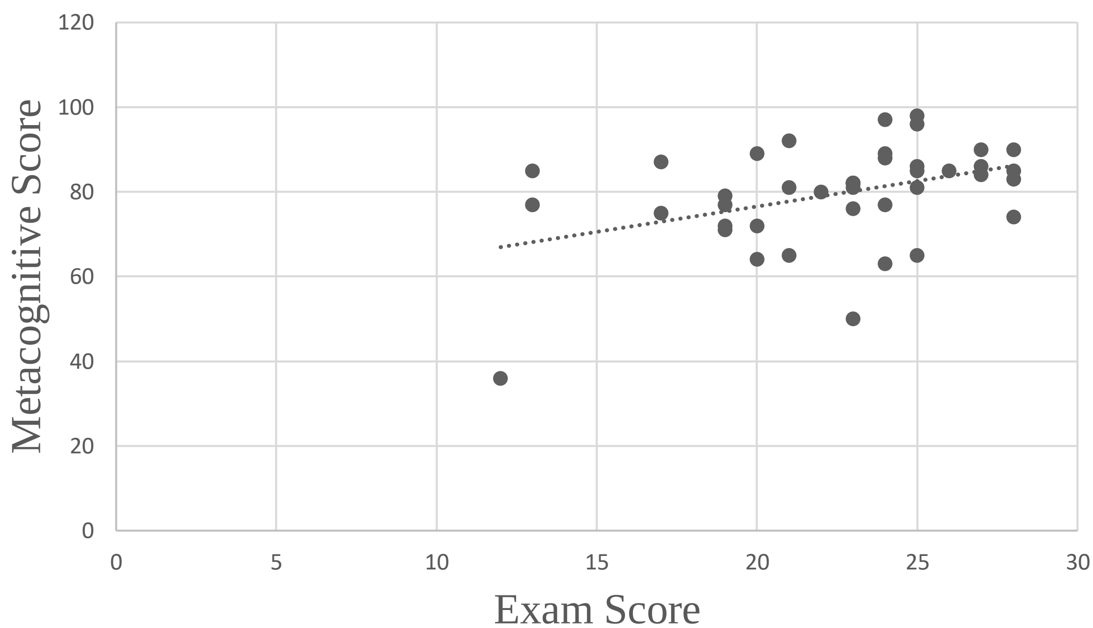

Figure 7. Scatterplot of metacognitive score of known information by exam score. Solid dots represent individual student data. The dashed line represents the trend line of the data for the equation $y = 1.1518x + 49.234$.

Students who had higher levels of confidence in their correct answers were able to perform better on the exam than students who did not have increased confidence. This confidence, perhaps, may stem from students who have studied more or have more prior knowledge of the subject matter, thus giving them more confidence when taking the exam. It could also arise from students who were more serious than others in answering the metacognitive confidence questions found under the subject matter questions on the LearnSmart screens.

The information produced from the third research question was surprising. Students who had prior experience using LearnSmart performed 9.88 % lower on the exam than students who did not have prior experience using LearnSmart. It was the assumption of the researcher that students who had prior experience using LearnSmart before this study would perform higher on the exam. This assumption was grounded in the belief students who had previous experience would exert less cognitive load overall in completing the LearnSmart modules since those students would not have to learn how to use and navigate the ALT in addition to answering questions pertaining to the subject matter (Chew, 2014; Tanner, 2012). The results indicated students who had prior experience using LearnSmart performed worse on the exam compared to students who had no prior experience using LearnSmart before the study.

It is difficult to understand why students who were new to the ALT performed better, but the difference could be caused by the increased effort the students who had no prior experience put forth, thereby actually increasing their learning through the fundamental metacognitive, constructive, and active learning theories (Chew, 2014; Engestrom, 2014; Freeman et al., 2014; Huntsberry, 2015; Isaacs, 2015; Jensen et al., 2015; Müller et al., 2015; Piaget, 1972; Tanner, 2012). Students who have used the ALT before may have become bored or complacent in their efforts to complete the assignment accurately. Perhaps the modules had become routine or students learned techniques to answer the questions faster than students who had not used the ALT before.

Implications for Practice

Based on the findings in this study, the use of the ALT, LearnSmart, produced statistically significant improvements in exam scores when used as a mandatory assignment prior to the exam. This finding is consistent with several other ALT studies that have taken place in other disciples at higher-education institutions (Cooke et al., 2008; Fletcher, 2013; Griff & Matter, 2012; James, 2012; Lee et al., 2011; McGraw-Hill Education, 2015; Phillips & Johnson, 2011; Waters, 2014). Adding preparatory assignments that involved the use of generation and active learning have been shown to increase student engagement and performance (Bertsch & Pesta, 2014; Engestrom, 2014; Freeman et al., 2014; Jensen et al., 2015; Van Blerkom et al., 2006).

Generation, even in small amounts, fosters a learning environment that forces students to have ownership over the material (Bertsch & Pesta, 2014; Engestrom, 2014; Freeman et al., 2014; Jensen et al., 2015; Van Blerkom et al., 2006). Since generation exercises involve active learning, students show higher levels of engagement, thus yielding higher performance (Bertsch & Pesta, 2014; Engestrom, 2014; Freeman et al., 2014; Jensen et al., 2015; Van Blerkom et al., 2006). Adaptive learning technology is active and contains various forms of generation (Bertsch & Pesta, 2014; Engestrom, 2014; Freeman et al., 2014; Jensen et al., 2015; Van Blerkom et al., 2006), and ALT has the ability to elevate student engagement and adapt the material to each student. Students in whole-group learning environments have the benefit of a personalized learning tool to help them. It would be the recommendation of the researcher to apply the use of an ALT as a mandatory assignment prior to an assessment in introductory business courses.

Additionally, based on findings from research question two, more emphasis on metacognition should be required in instructional strategies. Students who had a better understanding of what they actually knew and what they did not know were able to perform better on the assessment. The addition of LearnSmart should be made with concentrated efforts by the instructor to make students keenly aware that honesty in answering the metacognitive confidence indicators can help the ALT determine the appropriate personalized learning pathway for the student, thus resulting in the possibility of better exam performance. Perhaps this same philosophy of honesty in answering the confidence indicators could also have another benefit to students by creating self-awareness of their own level of readiness. This self-awareness phenomenon is the cornerstone of metacognition.

Recommendations for Future Research

There are several areas of this study that could be altered or modified in future studies in order to curb the limitations and make known the unknowns that still exist pertaining to the use of ALTs in introductory business courses. The following section details the modifications that could be made to future studies. The discussion of the modifications is organized by systematic groupings.

Population and sample demographics. This study encompassed three large community colleges in the Midwest. The small sample size relative to the number of students actually enrolled in introductory business courses across the United States is small; therefore, studies that involve a much larger sample size would increase the power and validity of the study (Seltman, 2015). The introduction of a larger sample size would also reduce sample bias, since larger sample sizes help bring the results of the sample studied more in line with the total population (Bluman, 2014; Fraenkel et al., 2011, Navidi & Monk, 2014). Furthermore, the study could be replicated at smaller institutions and at larger universities to compare the impact of the ALT on varying class sizes and populations of students. The study could be replicated at institutions that have varying levels of admission standards.

Another factor to consider for future research would be the geographic enlargement of the study to include institutions from different regions of the country. This study included three institutions in the Midwest, but the results of the study might be different if institutions from the East Coast or West Coast were introduced (Bluman, 2014). The inclusion of additional institutions from new geographic regions would also increase the sample size, thus, as mentioned above, increasing power and validity of the research (Seltman, 2015). Additionally, research that included four-year colleges and universities would also be an area of study to consider in order to create a sample more representative of the overall population of students enrolled in the introductory business course (Bluman, 2014; Fraenkel et al., 2011; Navidi & Monk, 2014).

This study did not take into account any differences in the student population. There were no distinctions made for the age, gender, experience in college courses, major, classroom seating arrangement, time of day of the course, or other factors. Additional research to find differences in these variables would be helpful, since researchers have indicated differences may well exist between these variables (Brown, 2014; Kang, Lundeberg, Wolter, delMas, & Herreid, 2012; Yang, Becerik-Gerber, & Mino, 2013). Research to find differences amongst age, gender, and the other factors listed above could possibly help identify new instructional strategies that might prove effective to increase learning (Kang et al., 2012; Yang et al., 2013).

Research design. The design of the study was created initially to assess the impact on exam scores in introductory business courses when different time increments of the ALT were used. Instructors assigned the two LearnSmart modules to students with an exam that followed. In future studies, limitations could be placed on when the modules would be completed in relation to the time the exam was given in order to probe the general implications of the proximity of the lesson to the assessment. There may be useful information pertaining to knowledge retention obtainable from studies that have a delayed time period between the completion of the ALT modules and the assessment.

Future studies could include research to alter the number of chapters of the ALT that would be assigned to students. An increase in the frequency with which the ALT was used during the course is also an additional modification that could be explored by researchers. Instructors could introduce the ALT early in the course to allow students more time to learn how to use and adjust to the program, and then researchers could assess the impact on grades throughout the course.

Additionally, researchers in the future could randomize the assignment of students in each section into one of the three groups. This would create a scenario in which students in all three groups would be able to be present for the exact same lecture and classroom environment. This method would thereby eliminate the limitation in this study that all instructors taught each section the same way. Efforts to limit potential contamination or sharing of information between students assigned to the different time groups would need to be addressed, but the data yielded from three randomized intra-class groups would be beneficial to research in the field.

There are several ALTs available on the market designed for introductory business courses in addition to LearnSmart (Fletcher, 2013; Riddle 2013). Additional research could be conducted using different ALTs under the same conditions as this study in order to assess the impact of the ALT. Perhaps randomizing each section of students and assigning a different ALT would yield interesting results. Additionally, students could be randomly divided in each section and assigned to different ALTs in order to assess exam score impact.

Beyond the limits of a quantitative study, additional research using qualitative methods could produce valuable data about the thoughts and feelings of students and instructors using ALTs. A small amount of qualitative research exists in the field pertaining to the implementation of ALTs at institutions of higher education (Gallagher, 2014), but future studies could seek to determine whether the ALT implementation was successful after its initial introduction. Future research using a mixed-methods approach may produce information about the effectiveness of the ALT from a quantitative measure as well as from measurements that are more difficult to measure by numbers alone.

Instrument. The unit exam consisted of 30 multiple-choice and true-false questions, which was relatively small compared to a very large number of questions that could be asked about the topic to measure learning. Furthermore, multiple-choice and true-false questions are only two types of learning assessment out of the many types of questions that could potentially be used to assess learning (Dennehy, 2014). The use of other forms of assessment could potentially capture student learning in ways that multiple-choice and true-false questions do not (Dennehy, 2014).

Summary

The gauntlet was thrown down in the early 1980s after Bloom (1984) highlighted a significant increase in learning in students who were provided a one-on-one, personalized learning environment compared to whole-group instructional strategies. In order to create this personalized learning environment many schools turned toward technology (Bain & Weston, 2012; Clark & Feldon, 2014; Huntsberry, 2015; Reich, 2014; Webley, 2013). Often, the efforts to introduce technology to the classroom were not effective in producing learning increases and were sometimes cost prohibitive (Bain & Weston, 2012; Clark & Feldon, 2014; Fletcher, 2013; Huntsberry, 2015).

As technology advancements increased, the costs of the technologies decreased, and technologies have been improved by developers and better used by instructors and students which has produced positive learning results (Dietvorst et al., 2014; Dornisch, 2013; Education Growth Advisors, 2014; Fletcher, 2014; Horn 2012; Huntsberry, 2015; Riddle, 2013; Waters, 2014; Webley, 2013; Zimmer, 2014). What once was called the "iron triangle" (Education Growth Advisors, 2014, p. 2) of cost, effectiveness, and availability, has now become penetrable with new technologies that have shown great promise at lower costs (Cooke et al., 2008; Fletcher, 2013; Griff & Matter, 2012; James, 2012; Lee et al., 2011; McGraw-Hill Education, 2015; Phillips & Johnson, 2011; Waters, 2014).

Adaptive learning technologies have emerged over the last two decades (Fletcher, 2013; Horn, 2012). The developers of ALTs have tried to create a personalized learning path through the use of complex algorithms that seek to understand student knowledge based on metacognitive variables (Chew, 2014; Fletcher, 2013; Horn, 2012; McGraw-Hill Education, 2015; NEJM, 2014). This study was created in order to assess the effectiveness of the ALT, LearnSmart, when used in an introductory business course at higher-education institutions. The population in the study consisted of nine sections of an introductory business course at three large community colleges in the Midwest. The primary information sought by the researcher was the effectiveness of the ALT on exam scores when used before a unit exam in the course, the ability to find a correlation between student metacognition in the subject matter and exam score performance, and the impact of having prior experience using the ALT prior to the study.

A one-way ANOVA was used to determine if a statistically significant difference would be found among the three groups. According to data from the one-way ANOVA, there was a statistically significant positive increase in exam scores in the group of students who used the ALT, LearnSmart, for 40-minute increments per chapter prior to the exam compared to the students who did not use the ALT. The results of the one-way ANOVA also support the anecdotal data McGraw-Hill Education (2015) reported in which students score 10.8% higher in courses that require LearnSmart as a mandatory assignment. The data also led the researcher to confirm higher levels of metacognition correlated to higher exam score performance. Lastly, there did not appear to be a direct statistically significant bearing on exam scores of students who had prior experience with the ALT. Based on the findings, the researcher concluded with Bloom's (1984) findings in which students in one-on-one learning environments have an advantage in learning compared to those students who learn in traditional whole-group learning environments.

The findings in this study could be used by instructors in order to create future instructional strategies and curriculums designed to increase learning. The study could also be used by school administrators to assist in determining if adding an ALT to curriculums would be beneficial. In addition, the creators of ALTs could use this study to tailor future algorithms and user interfaces to yield better learning results. Instructors who are seeking to add meaningful homework assignments to their instructional plans should consider the addition of the ALT, LearnSmart, in order to increase learning as evidenced in this study.

Appendix A

Informed Consent Form

LINDENWOOD

INFORMED CONSENT FOR PARTICIPATION IN RESEARCH ACTIVITIES

"An Evaluation of an Adaptive Learning Tool in an Introductory Business Course"

Principal Investigator: Tim Rogers
Telephone: [redacted] E-mail: TAR224@lindenwood.edu

Participant________________________ Contact info ___________________________

1. You are invited to participate in a research study conducted by Tim Rogers under the guidance of Dr. Kathy Grover. The purpose of this study is to determine if using the adaptive learning technology (ALT), LearnSmart, in seated introductory business courses at higher-education institutions will significantly have an impact on exam scores; and if a correlation exists between a student's metacognition in answering LearnSmart questions and performance on the exam.

2. a) Your participation will involve
   - Granting your instructor permission to share Chapter 17 and Chapter 18 de-identified data with the Primary Investigator (PI).
   - Completing one of three instructional plans for Chapters 17 & 18 as directed by your instructor.
     - Instructional Plan 1: Completing the regularly-scheduled exam for Chapters 17 & 18.
     - Instructional Plan 2: Completing a 20 minute LearnSmart module for Chapter 17, completing a 20 minute LearnSmart module for Chapter 18, and then completing the regularly-scheduled exam for Chapters 17 & 18.
     - Instructional Plan 3: Completing a 40 minute LearnSmart module for Chapter 17, completing a 40 minute LearnSmart module for Chapter 18, and then completing the regularly-scheduled exam for Chapters 17 & 18.

   b) Your instructor has incorporated one of the instructional plans listed above into the course as part of your course requirements. Therefore, you will have no additional time requirements outside of your course assignments.

   Approximately 350 to 1000 students will be involved in this research at three colleges/universities.

3. There are no anticipated risks associated with this research. If you are placed in the group that is not assigned the LearnSmart modules, and you perceive this to be a disadvantage in taking the exam, you will have the option to complete an exam with the use of the LearnSmart modules after the study.

4. There are no direct benefits for you participating in this study. However, your participation will contribute to the knowledge about adaptive learning technologies and may help society by helping researchers to find ways to increase learning overall.

5. Your participation in having your data collected and analyzed is voluntary and you may choose not to participate in having your data collected in this research study or to withdraw your consent at any time. Because the LearnSmart modules and the exam are worth points in your class, it would be in your best interest to complete all of the assignments and the exam. You will NOT be penalized in any way should you choose not to participate in having your data collected.

6. We will do everything we can to protect your privacy. As part of this effort, your identity will not be revealed in any publication or presentation that may result from this study and the information collected will remain in the possession of the investigator in a safe location.

7. If you have any questions or concerns regarding this study, or if any problems arise, you may call the PI, Tim Rogers, or the Supervising Faculty, Dr. Kathy Grover (417-881-0009). You may also ask questions of or state concerns regarding your participation to the Lindenwood Institutional Review Board (IRB) through contacting Dr. Marilyn Abbott, Interim Provost at mabbott@lindenwood.edu or 636-949-4912.

I am 18 years old or older, and I have read this consent form and have been given the opportunity to ask questions. I will also be given a copy of this consent form for my records. I consent to my participation in the research described above.

________________________________ ________________________

Participant's Signature Date Participant's Printed Name

________________________________ ________________________

Signature of Principal Investigator Date Investigator Printed Name

Appendix B

Exam Instrument

Exam Instrument (Chapters 17-18)

1. In order to increase the return on your money, you must invest in investments that have a greater chance at a higher rate of return, like mutual funds and stocks.
   A) True
   B) False

2. Having assets that depreciate quickly (like new cars) will help you to become wealthy quicker than buying assets that have little depreciation.
   A) True
   B) False

3. Which of the following highlights a firm's spending plans for the purchase of major assets?
   A) Capital budget
   B) Operating budget
   C) Cash budget
   D) Surplus budget

4. Delaware Aluminum Company uses its stock of unsold aluminum products as collateral for short term loans. This arrangement represents:
   A) Secured loans
   B) Revolving credit agreements
   C) Factoring
   D) Unsecured loans

5. Felicia is a public accountant. She has been asked to prepare the financial statements for McNick's Auto Body Shop. She is at the stage of the accounting cycle where she wants to summarize all of the data in the balance sheet to see whether the figures appear to be correct and balanced. After Felicia prepares the income statement, she will need to prepare a statement of cash flows in order to complete the financial statements.
   A) True
   B) False

6. Pulse rate and blood pressure can indicate a person's health. Similarly, _________ can reveal the health of a business.
   A) financial statements
   B) production schedules
   C) performance appraisals
   D) databases

7. The rate of return a company must earn in order to meet the demands of its lenders and expectations of its equity holders is called the:
   A) Leveraged capital
   B) Promissory note
   C) Cost of capital
   D) Venture capital

8. A line of credit that is guaranteed but usually comes with a fee is called:
   A) Revolving credit
   B) An unsecured loan
   C) Line of credit
   D) A secured loan

9. If you are buying ceiling fans from Harbor Breeze for $30 each and reselling them for $50 each, then your cost of goods sold (COGS) for each fan would be:
   A) $20
   B) $30
   C) $40
   D) $50

10. If a company issues bonds to raise money without having any collateral to back those bonds up with, they are called ___________ bonds.
    A) secured
    B) collateral-backed
    C) debenture
    D) ex post facto

11. Capital expenditures are considered major investments in long-term assets.
    A) True
    B) False

12. The income statement reports the difference between a firm's assets and its liabilities as of a certain date.
    A) True
    B) False

13. The budget that ties together the firm’s other budgets and summarizes its proposed financial activities is called the:
    A) operating master budget
    B) cash budget
    C) capital budget
    D) budget

14. The area of accounting that provides managers of an organization with information they need to make decisions is called:
    A) Tax accounting
    B) Managerial accounting
    C) Informational accounting
    D) Financial accounting

15. The fundamental accounting equation is:
    A) E=MC^2
    B) A=L+OE
    C) A=L+A
    D) L=A+OE

16. ____________ refers to the process that identifies financial variances by comparing actual revenues and expenses to projected/budgeted revenues and expenses.
    A) Factor analysis
    B) Forecasting
    C) Financial planning
    D) Financial control

17. The two major types of financing are debt and equity.
    A) True
    B) False

18. Items that can or will be converted into cash within one year are referred to as:
    A) fixed assets
    B) current assets
    C) tangible assets
    D) quick assets

19. If you buy a Lexus for $65,000, and then sell it 5 years later for $15,000, the loss of value is called depreciation.
    A) True
    B) False

20. To be sure that each company doesn't have a completely new way of keeping track of revenues and expenses, the FASB created these set of rules that must be followed when publishing financial statements.
    A) DKNY
    B) GAAP
    C) NYSE
    D) Nasdaq

21. A short-term forecast is a projection made for five-year increments.
    A) True
    B) False

22. The act of reviewing and evaluating the information used to prepare a company's financial statements is called:
    A) a CPA
    B) a CIA
    C) auditing
    D) the accounting cycle

23. Usually, the safer the investment, the ______ the interest rate is:
    A) higher
    B) lower

24. Rent, salaries, insurance, and depreciation are all examples of the cost of goods sold.
    A) True
    B) False

25. Debt financing must be repaid.
    A) True
    B) False

26. Unsecured short-term loans a bank will lend to a business, provided the funds are readily available, are called:
    A) Line of credit
    B) Secured loans
    C) Revolving credit
    D) Unsecured loans

27. Raising funds through borrowing to increase a firm's rate of return is called:
    A) Equity financing
    B) Capital budgeting
    C) Leverage financing
    D) Financial control

28. Maryland Nursery offers its customers credit terms of *3/15 net 30*. This gives customers a:
    A) 15 percent discount if they pay in 3 days.
    B) 3 percent discount if they pay in 30 days.
    C) 3 percent discount if they pay in 15 days.
    D) 15 percent discount if they pay in 30 days.

29. Bonds, loans, and other debt-financing instruments pay:
    A) Interest
    B) Dividends
    C) Yields
    D) Capital gains

30. If a firm has $100,000 in assets and $62,000 in liabilities, then the owner's equity is equal to $162,000.
    A) True
    B) False

Appendix C

Institutional Review Board Approvals

LINDENWOOD

LINDENWOOD UNIVERSITY ST. CHARLES, MISSOURI

DATE:	December 4, 2015
TO:	Tim Rogers
FROM:	Lindenwood University Institutional Review Board
STUDY TITLE:	[785334-1] An Evaluation of an Adaptive Learning Tool in an Introductory Business Course
IRB REFERENCE #:	
SUBMISSION TYPE:	New Project
ACTION:	APPROVED
APPROVAL DATE:	December 4, 2015
EXPIRATION DATE:	December 4, 2016
REVIEW TYPE:	Expedited Review

Thank you for your submission of New Project materials for this research project. Lindenwood University Institutional Review Board has APPROVED your submission. This approval is based on an appropriate risk/benefit ratio and a study design wherein the risks have been minimized. All research must be conducted in accordance with this approved submission.

This submission has received Expedited Review based on the applicable federal regulation.

Please remember that informed consent is a process beginning with a description of the study and insurance of participant understanding followed by a signed consent form. Informed consent must continue throughout the study via a dialogue between the researcher and research participant. Federal regulations require each participant receive a copy of the signed consent document.

Please note that any revision to previously approved materials must be approved by this office prior to initiation. Please use the appropriate revision forms for this procedure.

All SERIOUS and UNEXPECTED adverse events must be reported to this office. Please use the appropriate adverse event forms for this procedure. All FDA and sponsor reporting requirements should also be followed.

All NON-COMPLIANCE issues or COMPLAINTS regarding this project must be reported promptly to the IRB.

This project has been determined to be a Minimal Risk project. Based on the risks, this project requires continuing review by this committee on an annual basis. Please use the completion/amendment form for this procedure. Your documentation for continuing review must be received with sufficient time for review and continued approval before the expiration date of December 4, 2016.

Please note that all research records must be retained for a minimum of three years.

[redacted]

October 13, 2015

Institutional Review Board
Lindenwood University
209 S. Kingshighway
St. Charles, MO 63301

Dear Lindenwood IRB,

As a representative of [redacted], I confirm that the college grants permission for the proposed research, An Evaluation of an Adaptive Learning Tool in an Introductory Business Course, to be conducted by Timothy Rogers, once IRB approval or exemption has been granted. If you have questions regarding the content of this letter, please contact me at [redacted].

Sincerely,

[redacted]
College Director of Research and Strategic Planning

Hi Tim,

We have determined that your proposed research project is exempt from our normal IRB review process, under OHRP guidelines, given that it involves only *"research conducted in established or commonly accepted educational settings, involving normal educational practices, such as (i) research on regular and special education instructional strategies, or (ii) research on the effectiveness of or the comparison among instructional techniques, curricula, or classroom management methods"* (from OHRP website, 45 CFR 46). Please feel free to forward this e-mail to your degree-granting institution.

I wish you luck with your data collection.

[redacted]

Human Subjects Review

Proposal Title: An Evaluation of an Adaptive Learning Tool in an Introductory Business Course
IRB # 15-06

Dear Mr. Rogers and Dr. [redacted]:

Your research proposal has been approved by the Institutional Review Board at [redacted]. It is the IRB's opinion that you have provided adequate safeguards for the welfare of the participants in this study.

You are authorized to begin your research and implement this study as of the start date listed in your application, or the date of this communication if you listed the start date as "As soon as possible," "Upon IRB Approval," or a similar phrase. This authorization is valid until the end date listed in your application, or for one year after approval of your study, whichever is earlier. After this authorization runs out, you are required to submit a continuation or renewal request for board approval. For student research as part of a course, approval ends when the course ends unless the instructor/faculty sponsor notifies IRB in writing that supervision will continue, or if another faculty sponsor notifies IRB of assuming supervision responsibilities.

This approval is granted with the understanding that the research will be conducted within the published guidelines of the [redacted] Review Board and as described in your application. Any changes or modifications to the approved protocols should be submitted to the IRB for approval if they could substantially affect the safety, rights, and welfare of the participants in your study. Please use the IRB number in all your communications.

Thank you for sending us your application for research involving human subjects. By doing so, you safeguard the welfare of participants in your study and federal funding of our college.

Sincerely,
[redacted]

[redacted]
Co-chair, Institutional Review Board
[redacted]

Appendix D

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Mc
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Education

PERMISSION LICENSE: COMMERCIAL ELECTRONIC USE

Request ID/Invoice Number: TIM26532

Date: December 01, 2015

To: Timothy Rogers
Lindenwood University
209 South Kingshighway Street
St. Charles, MO 63301
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Vita

Tim Rogers currently teaches in the Business Department at Ozarks Technical Community College, in Springfield, Missouri. He holds a B.B.A. from Evangel University, in Springfield, MO, and an M.B.A. from the University of North Dakota, in Grand Forks, N.D. He has a strong passion for teaching and research. Prior to teaching, he worked in station operations for United Airlines, Northwest Airlines, and Delta Airlines. Through his experience in the airline industry, Tim was able to gain valuable knowledge that helped him write a case study, *United Airlines: A Strategic Perspective*, which was published in the North American Case Research Association. Following the airline career, Tim served as a stockbroker and financial advisor with a major investment firm. He holds his Series 7 and Series 63 securities licenses.

Outside of his working life, he enjoys traveling across the United States and around the world, having visited numerous countries on four continents. He enjoys restoring and driving classic cars. Tim holds his pilot's license and loves to fly whenever he gets the chance. He resides in Springfield, MO, throughout the school year and in North Dakota during the summers with his wife, Shelley, and two beautiful girls, Elyse and Sydney.