EVALUATION OF AN ADAPTIVE LEARNING TECHNOLOGY AS A PREDICTOR OF STUDENT PERFORMANCE IN UNDERGRADUATE BIOLOGY

A Thesis
by
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Submitted to the Graduate School
Appalachian State University
in partial fulfillment of the requirement for the degree of
MASTER OF SCIENCE

May 2012
Department of Biology

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ABSTRACT

EVALUATION OF AN ADAPTIVE LEARNING TECHNOLOGY AS A PREDICTOR OF STUDENT PERFORMANCE IN UNDERGRADUATE BIOLOGY

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With increased use of educational technologies comes the need to not only evaluate whether or not these technologies are effective, but also how instructors can utilize these technologies to adapt teaching practices for maximized student performance on formal assessments. This study examines four specific aspects (time, completion, metacognitive data, and a program-generated student score) of LearnSmart™, an adaptive learning technology developed by McGraw-Hill Higher Education, and the potential effects these aspects might have on student assessment performance. With a focus on data from a module on cellular respiration, this study examines relationships between LearnSmart™ use and student quiz and exam scores. The results indicate statistically significant relationships when the module student score, module completion, total time spent on all LearnSmart™ exercises, and total average percent completion are used as predictors for exam score. Though other trends existed, most LearnSmart™ data is not a statistically significant predictor of assessment performance on a group level ($p < 0.05$). Overall, however, all LearnSmart™ data can provide a very useful tool for student self-reflection and for one-on-one interactions between instructor and student, including advising. Finally, in conjunction with data gathered from an optional LearnSmart™ student usage survey, and experience teaching and learning with LearnSmart™, the study concludes with best practices for instructors with regard to adaptive learning technology.

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ACKNOWLEDGEMENTS

First, I would like to thank the Cratis D. Williams Graduate School, particularly the faculty and my peers in the Biology Department. I would also like to thank my advisor and committee co-chair, Dr. Michael Windelspecht, for his constant encouragement, without which I probably would not have returned to Appalachian in pursuit of my graduate degree. Michael has been supportive in my educational, professional, and personal life since I was an undergraduate at Appalachian. I attribute much of my success to his assistance. I would like to thank committee co-chair Dr. Jenni Geib and committee member Dr. Ted Zerucha, for their endless patience, flexibility, and advice. Thank you all for taking a journey on a bit of a different thesis project for the sciences. In addition, I would like to thank Dr. Jim Barbee for his assistance, particularly for being patient and flexible as well.

I would also like to thank my colleagues at McGraw-Hill Higher Education for the opportunities they have provided me, for allowing me to use their adaptive learning platform as the subject of my research, and for being professionally and personally supportive of me throughout the development and execution of my thesis research.

I would like to extend a special thank you to my family, my friends, my employers and co-workers, and especially to Rob Tallant for being supportive and tolerant of my near-constant pre-occupation with my computer and my work.

INTRODUCTION

The ultimate goal of education is to facilitate the learning process. From young children to students of higher education, effective instruction is the basis of quality learning. Unfortunately, in our current environment, education is struggling at all levels to provide truly effective instruction, resulting in poor student performance, low student retention, and an overall dissatisfaction with the education system. In response, a nearly constant effort has been devoted to reforming, and thus improving, education. At the classroom level, these efforts focus primarily upon instructional tools and strategies that aim to enhance student engagement and increase student performance. However, despite continuous efforts made to make instruction more effective, classrooms become increasingly crowded and instructor workloads grow to match.

The major challenge that results from rapidly increasing class size is a lack of personalized instruction, which is a problem considering that individualized instruction is associated with the highest levels of student performance. Proponents for individualized instruction include Benjamin Bloom, well-known for his educational theories and Bloom's Taxonomy, who reported in a 1984 study that one-on-one instruction improves student achievement by two standard deviations over group instruction (Bloom, 1984; Kidd, 2010; Vandewaetere *et al.,* 2011). Though the challenges are many and are not necessarily specific to subject matter, the focus herein will be on the individualization of instruction in the undergraduate biology classroom.

Universities and colleges alike are seeing poor student performance while also losing students from the sciences, both as non-majors and intended majors. The reasons for this are undoubtedly numerous, but the solutions are simple, in theory: good teaching results from personalized, one-on-one interaction between an instructor and a student. The challenge in achieving good teaching, especially on college campuses, lies in the variation in science background among college students, the increasing number of students per course section, the short time an instructor has to get to know his students, the near impossibility of tailoring a course to each individual's needs, and the high probability that a poor first-semester introductory biology experience will discourage a student from continuing in the sciences (Paramythis & Loidl-Resiinger, 2003).

In many cases, these challenges are simply ignored. For example, sometimes instructors do not attempt to tailor a course at all, instead continuing to teach the same material in the same manner as they did not only the previous semester, but every semester before. In other cases, standardization of course content suffers: At institutions with multiple instructors, a failure to establish a standardized curriculum, which addresses the same set of specific learning outcomes, often results in a lack of consistency between courses, frequently leaving some students less prepared than others to progress to higher level science courses (Cheeseman *et al.*, 2007). Still, another challenge exists in addressing the ever-increasing volume of content in an introductory biology course (Cheeseman *et al.*, 2007; O'Toole & Schefter, 2008; Windelspecht, 2001).

Frequently, when an instructor does attempt to address these educational challenges, a diagnostic exam might be administered. Subsequently, the instructor would attempt to tailor the course content, focusing on areas of weakness and de-emphasizing or skipping areas that have been mastered by most of the group, based upon the diagnostic results. The potential issues with this method include the design and execution of the exam itself, and the level of student investment in the exercise. Under circumstances with poorly designed or administered exams, and/or low student investment in the diagnostic, the exam (usually an in-class ungraded assessment) can be a waste of class time, and may fail to effectively portray a student’s background knowledge and areas of strength and weakness. Thus, sometimes even when an effort is made to make student-centered teaching adjustments, the challenges can remain in most classrooms.

As the volume of content to disperse and the student enrollment grow, other important changes are taking place in education. Established instructional standards are constantly being evaluated and changed, many coming to include digital learning tools. As education becomes geared more towards digital learning, the fields of education and technology find themselves coming together to create engaging, accessible, reusable learning tools. Technology in the classroom is promising, and it is in demand, though it brings with it a unique set of challenges. It requires instructors to rethink in-class and online teaching methods, and to decide how they will go about engaging the online student (Salazar, 2010; Windelspecht, 2001). However, because current in-class instructional approaches are unable to deliver the appropriate level of individualized learning (differentiation), integration of technology seems the best candidate for providing the ideal of personalized learning. Technology can offer educational experiences tailored to student "needs, goals, talent and interests" (Klasnja-Milicevic *et al.*, 2011). And, in conjunction with the added option to deliver coursework partially or entirely online, the burden of a specified time and place for learning is also being eliminated. Though its official definition varies, the concept of computer-assisted personalized learning is termed adaptive learning, or adaptive learning technology.

Development of Adaptive Learning Technology

Like any good teaching tool, adaptive learning technology (ALT) has been developed with the characteristics of its audience in mind. Thus, effective virtual learning technology has been created based on what we know about real learners and learning. Multiple adaptive learning platforms have been designed based on premises of how learning happens. Though many learning theories exist, none is especially formulated to support learning through ALT (Pange & Pange, 2011). The underlying premises about learners and learning upon which adaptive technologies are based include cognitive development, knowledge construction, and theories of knowledge representation.

Cognitive Development. The Swiss psychologist Jean Piaget is perhaps the best-known investigator of cognitive development. As a result of his studies of young children, Piaget came to many conclusions surrounding the stages of thinking ability that progress from infancy to adulthood (Byrnes, 2007). Piaget studied language, thinking, perception, attention, and memory, and examined the integration of these functions for learning and problem solving, or cognitive processes. Cognitive development, a change in these functions and processes over time, became a widely studied phenomenon. Thus, many theories on cognitive development and learning exist.

In his third edition of “Cognitive Development and Learning in Instructional Contexts”, James P. Byrnes (2007) explores six theories of cognitive development and learning. Through the ideas of Edward Thorndike, information processing theorists, connectionists, Jean Piaget, schema theorists and Lev Vygotsky, the text explains that despite the existence of multiple theories, a few overarching themes surround cognitive development and learning. These themes include: 1) repetition and practice; 2) meaningful, goal-directed learning; and 3) the role a student’s previous experiences and knowledge play in their learning style.

Practice. Repetition and practice are thought to serve to strengthen or modify associative bonds formed during learning, aiding in the internalization of skills and formation of meaningful abstractions (Byrnes, 2007). Practice is an important aspect that must be built into any ALT. Virtual flashcards and other repetitive practice exercises are used to provide practice in ALT. These exercises might cover anything from important vocabulary to concepts central to the chapter or unit of study, and frequently utilize fill-in-the blank and/or matching formats.

Meaningful, Goal-Directed Learning. As students are learning new material, partly through repetition and practice, they must integrate their new knowledge into their current knowledge, since the learning process is more successful when it is meaningful to the student. Meaning can be built into learning when the interests of the student are considered and included in scenarios or other examples used for instruction.

In attempts to achieve meaningful, goal-directed learning using ALT, many platforms include some form of a “learning plan”. This plan may be based upon a diagnostic exercise, or could be an established lesson set up by an instructor. The purpose of the learning plan is to provide the student with a visual representation of where they will start and end, and what steps they will take in their learning. It might also provide built-in deadlines or other time-related goals.

Learning Style. A plethora of teaching strategies exist, in part because different students learn in different ways. Examples of learning styles are visual, auditory, and hands-on (also termed tactile or kinetic). That is to say, some people learn primarily from what they see, some from what they hear, and others from what they do. In most cases, learners use one or more of these styles to learn best. ALT addresses different types of learners by incorporating a mixture of visual, auditory and virtually tactile activities. The visual element might incorporate anything from text formatting to figures, videos, tutorials, or other art used to teach. An auditory element can be included in ALT through spoken definitions of vocabulary words, videos, or other animations with recorded information. To incorporate elements useful for tactile learning, figures and other art can be designed such that the learner can manipulate their parts. This could include physically clicking and dragging words to fill in blanks or match definitions, moving events in a process into a logical sequence, or building a structure from its subsequent parts. Potentially, virtual labs may also meet the needs of tactile learners by allowing them to virtually carry out any activity one might perform in a lab (dissection, mixing chemicals, etc.).

Learning style must be considered when designing instruction. With regard to learning, Byrnes (2007) defines cognitive development as an increase in cognitive ability with age. The acquisition of knowledge, thus, happens slowly over time. And because learners slowly change as they get older, instruction must also change, resulting in different teaching techniques at different grade levels. Even within grade levels, however, all learners do not change in the same ways at the same time. Thus, there is not a single instructional technique that works well for all students. Cognitive development creates a need for a multitude of instructional techniques within and among grade levels. The instructional approach used in an attempt to meet the cognitive, and motivational, needs of individual learners is termed differentiated instruction. Differentiation in instruction requires a functional understanding of the learner, to include educational experience or background and current levels of understanding, along with where the learner is headed.

Essentially, if an instructor knows what a student already knows and can do, and what they would like the student to know and be able to do by the end of a given instructional period, the next steps in the learning process can be tailored to be appropriately challenging. Instruction at the appropriate level or rigor prevents wasting instructional time on material that is below or above a student's ability level, which subsequently helps to keep the learner engaged. In experimenting with different designs for ALT, building in the ideas of learning style and automatically differentiated instruction has been an important goal.

Knowledge Construction: Constructivism. The constructive nature of learning, emphasized by Jean Piaget, schema theorists, and Lev Vygotsky, is based upon how a learner constructs knowledge (Byrnes, 2007). Constructivism denies that knowledge can exist outside a person and simply be transferred to them, as an objectivist, or a traditional lecture-giving instructor, might believe. Instead, constructivist theory describes how learners interpret reality and instruction (Byrnes, 2007). In this way, constructivism incorporates some of the ideas previously discussed with regard to meaningful learning. Piaget described processes, called *accommodation* and *assimilation*, through which individuals incorporate new experiences into an existing mental framework. As defined by Piaget, accommodation occurs when an individual must reframe their current understanding of the world to incorporate new ideas and experiences, whereas assimilation takes place when new ideas and experiences fit into an individual's existing framework, or when an individual fails to make changes to an existing, faulty, understanding. Because accommodation involves reevaluation of current understanding, it is thought to be one of the mechanisms by which failure leads to learning (Polycarpou & Vemuri, 1995).

As such, constructivism is often associated with active learning, or learning by doing. The role of an instructor in active learning is that of a facilitator instead of a traditional instructor (Bauersfeld, 1995). Instead of lecture, or other forms of instruction that involve a teacher "imparting knowledge", a facilitator asks questions and supports the learning process from the sidelines.

In his study of web-based learning, Zangyuan Own (2010) reports on a similar study conducted by F. Lin (2001), explaining that Lin's study (published only in Chinese) investigated web-based learning using the constructivist approach, finding that achievement was higher for college students in the sciences when compared with other students. The adaptive learning platforms explored in Lin's investigation, and others described as background in Own's 2010 study, use ALTs that change the learning process based upon a course's relevance to a student's field. "Story-telling" teaching is used for field-dependent courses, employing simulations and other tactics to help students learn by doing (Own, 2010).

Essentially, ALT that incorporates virtual forms of hands on activities, or situational learning that allows students to make choices that may lead them down one of several paths during the learning experience, are examples of constructivism in ALT. Virtual labs are examples of "hands on" activities. Situational learning might include virtual Emergency Medical Technician (EMT) training that provides hypothetical emergencies for student practice; the activity might include hypothetical patient descriptions, vital signs and symptoms, or other details that the student must evaluate and respond to. Depending on the response, the activity would adapt. For instance, if the student makes correct evaluations and chooses appropriate "treatments", the patient would "live"; if the student makes incorrect evaluations, the patient would "die". Constructivism in ALT can be very useful since it serves to put learning into context, to make learning a structured discovery process, and to engage and challenge the learner.

Knowledge Representation. Knowledge representation (KR) is an area of *artificial intelligence* (AI) research that explores the challenges of accurate and effective use of symbols to represent facts in a knowledge domain (Thomson, 2005; Martin, 2002). Knowledge is the term given to our mental representations of the world (Wilson & Keil, 2006). Outside the mind, this knowledge is represented physically through symbols, or meaningful patterns that can be manipulated. In creating ALT, thought is given to the roots of AI and *intelligent tutoring systems* (ITS), which first took on the challenges of representing knowledge with computers, based upon existing theories surrounding KR. These theories find their foundation in cognitive psychology and neuroscience, and include ideas like concepts and categories, semantic networks, and consideration for how information is stored and handled in the brain (Poole & Mackworth, 2010).

Organization is a key concept in KR. Concepts and categories, which help the human brain store information in an organized manner, include mental representations like memory and groupings of similar ideas. Just like they do in the human brain, concepts and categories help computers to more efficiently navigate the environment. Thus, in representing knowledge with computers, organization that mimics that of the brain is important. By creating categories of knowledge, the computer becomes “informed” and more capable of intelligent action. The challenges of training the computer, however, are clear if we consider the way the human mind forms generalized definitions when forming categories.

An example explored by Poole and Mackworth (2010) surrounds the category of “cars”. The human brain does not define cars as all objects that run on gasoline, or all objects with four wheels, though these definitions do describe many members of this category. Instead, we have a generalized definition of “cars” from our experience that allows us to include more members in the category. It is due to categories, at least in part, that we recognize an object we’ve never seen before. Otherwise, every car we saw that was not of the same make, model, color, (etc) would appear unique. Thus, though we can attempt to include all examples that fit into a category into a group for a computer to use as a resource, that computer will usually end up with a more limited category than the human brain.

The human brain goes a step further in organizing information. It is theorized that the brain structures categories in a hierarchy while also creating relationships between the categories. In this manner, all-encompassing larger categories can be split into smaller, more detail-oriented categories. These levels differ based upon criteria like expertise and culture, since an expert more closely examines the details of items in their field than a non-expert might. The “basic” level in a given area of interest is lower for an expert than for a layperson. The relationships we create are explained by the *semantic network approach*, which proposes that concepts of the mind are arranged in networks, or that we create meaningful connections between categories to create a functional storage system (Poole & Mackworth, 2010).

The human brain serves as an inspiration for computer science and development of computational systems, a process called knowledge engineering. In representing knowledge on computers, some think it best to represent it in the same way that it is represented in the mind, using human language. However, artificial languages and notations, based on logic and mathematics, have also been proposed. Many current adaptive learning platforms are built to represent knowledge in plain human language though they are built on websites that are coded. Despite the language, the challenge of KR is primarily how to store and manipulate knowledge in an information system in a formal way such that it may be used to accomplish a given task. This, of course, would be the goal of KR in ALT: using representations of knowledge in the pursuit of learning tasks which, in turn, might lead to new knowledge to be represented (Martin, 2002).

In designing ALT, one important goal is to create reusable learning objects; the more context-specific a learning object is, the less reusable it becomes. This is important when considering how specifically to symbolically represent knowledge with computers. Certain subject matter, for example a major subject at a high level, is better-suited to be designed such that KR is highly precise and detailed, while more general subject matter can use KR at a more generalized level. For example, take the visual symbols that might be used to represent a car: a car might be represented as a simple symbol if the structure of the car is not important to the subject matter. However, if the ALT is teaching mechanics, the details of the car are of much more importance. This same idea can be carried over to simpler symbols, like words and sentences. The levels of vocabulary and sentence structure built into a computer's KR are important aspects, which should be adjustable, when designing ALT.

Another example of KR in ALT comes back to the idea of semantic networks, and the organization of categories based on relationships between them. This idea can be applied to functions such as facilitating learner-created concept maps. Network-based KR can also assist in developing learning through many connections between knowledge, rather than a student reaching a solution only through single, linear methods. This network design might be employed, for example, in a constructivist (active learning) activity that gives students many possible paths from original question(s) to solution(s).

Designing ALT has been, and will continue to be, a challenging field that necessitates an understanding of technology, education, and ideas from a wide range of subject matter from cognitive psychology to neuroscience. The ultimate goal, however, remains; ALT seeks to virtually produce what can best be accomplished by one-on-one tutoring: personal, individualized instruction that takes the learner into account at every level. As such, the development of ALT has incorporated many of the underlying premises about learners and learning, including cognitive development, constructivism, and knowledge representation. With continued efforts to consider the needs of the learner, goals of high levels of achievement and constant reevaluation of current technology, ALT can continue to grow. This growth must rely in large part on best practices learned from classroom instruction, specifically that which incorporates ALT, as instructors discover what is most effective in practice for positively influencing student outcomes. The better instructors can come to understand how adaptive learning is influencing student learning, the more effectively they can fully exploit adaptive learning resources and technologies.

Defining Adaptive Learning Today

The literature currently defines adaptive learning in a variety of ways. Some definitions do not include the technological aspect at all, calling adaptive learning "the use of what is known about learners…through interactions, to alter how a learning experience unfolds" (Howard *et al.*, 2006). Most definitions, however, have come to incorporate the role of technology in the alteration of the learning experience (Vandewaetere e*t al.*, 2011). Despite its definition, the goal of adaptive learning is consistently expressed throughout the literature: be more responsive to learners as individuals (Howard e*t al.*, 2006).

In defining adaptive learning, the literature also presents the necessity of understanding *blended learning*, which has essentially coevolved with technology in the classroom. Blended learning, as defined by the distance learning community, acknowledges the complementary nature of synchronous (in class) learning activities combined with asynchronous (outside of class) learning activities. As of late, blended learning refers to the combination of in class lecture and other activities combined with online activities. Courses that are taught partially online and partially via face-to-face lecture are, thus, blended learning courses. This type of course, which is growing increasingly common (Wu *et al.*, 2010), is also referred to as a “hybrid” course. This type of course is the focus of the research presented in this thesis.

Examples of adaptive learning also cover a wide range and can include anything from an alteration in text size and color, to the incorporation of an audio dictionary, to the alteration of the actual content of learning materials, depending on the needs of the learner (Howard e*t al.*, 2006). These needs can be determined automatically as information is being gathered about the learner, to include characteristics like prior knowledge, learning style, and cognitive style. This may occur through surveys, pre-tests, and sample practice exercises. Later, a learner “profile” can be applied to future assignments. An adaptive learning system can be exclusively controlled by the instructor, share control between the student and the instructor, or take on an “open learner model” that allows for self-assessment by making the learner profile explicit to the learner. In the latter, the student may even alter their profile if they think it inaccurately represents one or more of his learning characteristics.

The instructor can alter aspects like whether or not questions incorporate hints, include instructor feedback for incorrect (or all) responses, offer remediation/review instructions for incorrect responses, or include or exclude time limits, for example. Using instructor modifications, an instructor can build scaffolding into an online activity by organizing exercises such that they progress from “easy” to “difficult”, whilst incorporating fewer support settings like hints and delivering more challenging content. Students can alter things like volume levels, text size and color, or add their own (personally perceived) learning characteristics if the system has not included them in the learner profile (Vandewaetere e*t al.*, 2011). Student controlled systems, however, must avoid becoming pools of questions organized by topic or chapter. This is because, in systems that operate in this manner, students often select exercises that are too simple or too complicated and they either become disengaged due to boredom or discouragement. A student-controlled system should aim to allow a level of student control that also provides optimal student learning.

Based on learner profiles, for instance, a large pool of questions could be automatically filtered to suit the level of the learner. The student is still able to exert control by selecting an exercise out of a pool, but the pool only includes questions at the appropriate level for the learner (Hsiao *et al.*, 2010). Programs that operate in this manner can ensure that lower level students focus on remediation and introductory exercise, while higher-level students progress through exercises to demonstrate their understanding of and ability to apply a concept (Own, 2010).

The benefits of incorporating technology into the classroom are plentiful. The use of this technology to facilitate adaptive learning magnifies its benefits. Some classroom technology is capable of providing an adaptive learning experience within the online learning environment by altering the pace of instruction, the level of materials assigned, and the types of questions asked, for example. The results of student interaction with the technology, in the form of quiz scores or individual item success rates, for instance, can then be used by instructors to further adapt the learning environment in the physical classroom.

Online learning can provide immediate correction and/or feedback to students when working on homework or other out of class activities, which has been shown to be beneficial to the learning process (Howard e*t al.*, 2006; Own, 2010). It also prevents students from spending too much time on an inappropriate level of material outside of class, while allowing an instructor to tailor lectures to the demonstrated specific needs of a specific group or groups of students.

Because of built-in scaffolding, students and instructors can examine the results of the student interaction with the online material to see where learning breaks down. As a result, a student can be made aware of topics to focus on in studying on their own, and when instructors are able to help students one-on-one, during office hours for instance, they have an online record that provides them a working knowledge of what a student did not understand or perform well on. The research presented here has its foundations in the adaptations that teachers and students can make in the learning process based on the tools available.

Adaptive Learning in Practice

The current literature offers, if only a few, applications of adaptive learning in practice in the form of case studies. Two of the strongest examples are summarized herein.

At the University of Taiwan, Zngyuan Own conducted a study of online exercises versus adaptive online exercises on oxidation and reduction reactions (Own, 2010). The authors sought to design and create an adaptive learning environment, gather quantitative evidence to compare the adaptive to the traditional web-based learning environment (with regards to a unit in life chemistry), correlate results with learning profile characteristics, and examine student satisfaction with the learning environment.

By examining two types of online learning environments, the study found that adaptive online learning outperforms non-adaptive online learning, that higher level students enjoy greater achievements in adaptive online learning, that male performance exceeds that of females, that science departments perform better than other departments, and that students who study longer in adaptive online learning environments have greater achievements.

Own's study draws attention to the need to fully exploit the characteristics of a learning medium to get the best results. In other words, adopting any web-based learning system and not using it correctly will not benefit the instructor or students. It encourages instructors to actually use the results of the medium to adapt their teaching habits.

In a project that looks at improving undergraduate biology courses by making them hybrid courses, Riffell and Sibley compare their hybrid course to a simultaneously offered traditional course (Riffell & Sibley, 2005). The study makes suggestions to identify the students that are best-suited for online learning, based on the results of multiple regression analyses of the relationship between a number of predictor variables (gender, freshman-senior status, major/non-major, commuter status, attendance, and experience with online courses) and student performance on a course post-test. Based on these results, the authors recommended hybrid learning to upper classmen seeking general science credit. The results find the hybrid course to be superior (by a letter grade, or 10% higher performance on the course post-test). It states that the best-suited student is the on-campus (residing on or near campus), non-majors upperclassmen. They also find that online assignments are equally if not more effective than classroom assignments, and that classroom-based exercises are more effective when coupled with online assignments.

Though the concept of adaptive learning is still relatively new, the literature is lacking in several ways. The majority seeks to define, redefine, or add to the definition of the term itself. Firm definitions of terms, including the term adaptive learning, are missing, as are standards for the implementation of adaptive learning technology. The largest gap in the literature is in the lack of publications regarding the application of adaptive learning strategies to a specific field of study or a specific course, or examining the application of adaptive learning to specific instructional units or learning outcomes. Thus, colleges and universities have very little empirical data on the differences in student outcomes in traditional, hybrid, and online courses.

Development of the Study

LearnSmart™ is an ALT platform created by Area9, and currently licensed to McGraw-Hill Higher Education (MHHE). The LearnSmart™ platform in embedded with MHHE's Connect platform, a next-generation content management system.

The premise behind the LearnSmart™ system is relatively simple. Almost all textbooks in higher education contain learning outcomes (or objectives) that define the core content knowledge that is expected of the student after completing a specific amount of material. LearnSmart™ expands on these learning outcomes through the use of "probes", which break the learning outcomes down into individual pieces of information a student must understand. For instance, a learning outcome for cellular respiration might read "Identify the inputs and outputs of cellular respiration." Probes for this learning outcome might include questions such as:

- What are the inputs and outputs of glycolysis?
- What are the inputs and outputs of the citric acid cycle?, or
- What are the inputs and outputs of the electron transport chain?

Whereas a single section in a non-majors introductory biology text may have 2-3 learning outcomes, the same section may possess dozens of specific probes. Each probe is, in turn, tied to a series of questions. The questions are tagged on a scale of 1-4, with category 1 representing important core knowledge and category 4 representing application-based or less-critical information. A category 1 probe for cellular respiration might read: “Identify the location of glycolysis”, while a level 4 probe might be something like “What happens if no oxygen is available for cellular respiration?”.

Figure 1 demonstrates a typical question within LearnSmart™. The key to LearnSmart™ is integrated into student self-assessment of their knowledge of the content. This assessment is performed using the four buttons directly under the card, which the student must respond to prior to attempting the question.

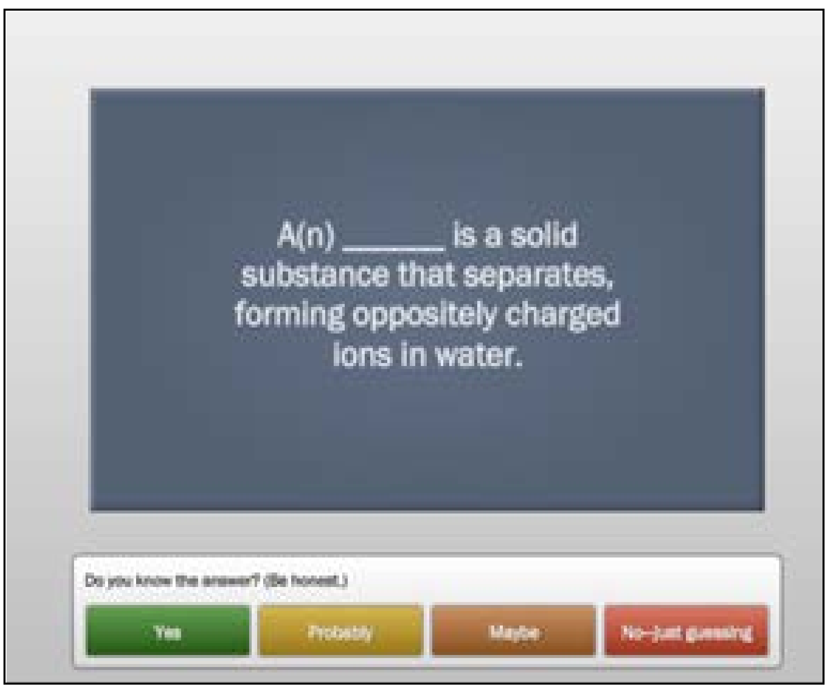

Figure 1. Screen shot of a typical LearnSmart™ question. The student must select a response to “Do you know the answer? (Be honest.)” before attempting to answer the question.

The student responses dictate the learning path through the material. For example, if a student answers a question correctly there are two possibilities: 1) the student knew the content, or 2) the student guessed correctly. Likewise, an incorrect response may be associated with a misunderstanding of the wording associated with the question, and not the subject content directly.

The artificial intelligence within LearnSmart™ recognizes these possibilities, and will return to core concepts (category 1 probes) from multiple perspectives to assess student comprehension. These perspectives might include asking a question first as a multiple choice item, and subsequently as a fill-in-the-blank/free response item. If a student consistently demonstrates a deficiency with a concept, the system will generate a brief "timeout" and direct the student to the location of this content in the textbook (either electronic or print versions).

It is important to note that students are not graded on a percent correct basis. Instead, the system focuses on percent completion. However, perhaps the most useful function of LearnSmart™ is the generation of metacognitive data, that is, data that reflect the student's perception of their understanding (Figure 2). Both the students and the instructors have access to these data, which can be used for self- or class-based assessment of content comprehension.

As instructors began to use LearnSmart™ , they also sought to evaluate its effectiveness. To do so, some performed rough analyses of average exam grades with and without the use of LearnSmart™. These studies (Windelspecht, unpublished), indicated a relationship between use of LearnSmart™ and an increase in student performance on formal assessments, namely mid-terms and final exams (Figure 3).

Case studies have also been conducted at a number of other institutions that use LearnSmart™. These studies, which can be found online at The Connect Community website (theconnectcommunity.com), show outcomes including increased student retention rates and higher average exam scores.

Sample report. Metacognitive skills

Student	Correct & aware	Correct & unaware	Incorrect & aware	Incorrect & unaware	E-mail
Student, 19	6%	61%	29%	4%	student19@mail.com
Student, 20	8%	77%	13%	1%	student20@mail.com
Student, 21	7%	65%	26%	3%	student21@mail.com
Student, 22	23%	54%	16%	7%	student22@mail.com
Student, 23	9%	74%	15%	2%	student23@mail.com
Student, 24	57%	26%	5%	12%	student24@mail.com
Student, 25	40%	47%	7%	6%	student25@mail.com
Student, 26	5%	62%	30%	4%	student26@mail.com
Student, 27	8%	74%	16%	2%	student27@mail.com
Student, 28	39%	21%	14%	26%	student28@mail.com
Student, 29	14%	73%	10%	2%	student29@mail.com
Student, 30	7%	60%	30%	3%	student30@mail.com
Student, 31	24%	64%	9%	3%	student31@mail.com
Student, 32	21%	36%	27%	16%	student32@mail.com
Student, 33	6%	55%	34%	4%	student33@mail.com

Figure 2. Sample metacognitive report.

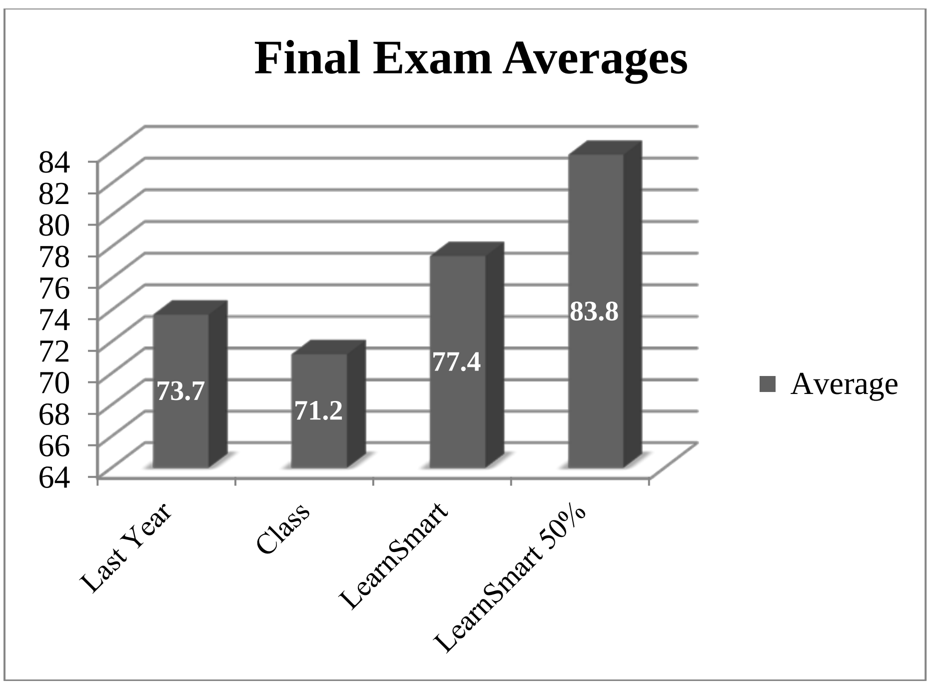

Figure 3. Effects of LearnSmart in Introductory Biology: Preliminary (unpublished) LearnSmart ™ data demonstrating the relationship between LearnSmart usage and final exam grades. Last Year = final exam average for previous year's class; Class = final exam average for current semester; LearnSmart = student who used LearnSmart at all; LearnSmart 50% = students who used half (or more) of all LearnSmart activities

Though the results of Windelspecht (unpublished) and the case studies found on Connect Community seem to suggest that LearnSmart™ is making an impact in the classroom, none of these studies provide quantitative data regarding specific usage patterns or highly influential components of LearnSmart™ that impact student retention, student performance, etc. Recognizing that LearnSmart™ appears to be positively influencing science education, this study sought to look more specifically at how LearnSmart™ might be causing the outcomes reported by the Connect Community case studies and Windelspecht (unpublished).

One of the virtues of LearnSmart™ is a wealth of automatically-generated data as a result of student interaction with the activities. These data are available in the form of several LearnSmart™ reports, which include information about the amount of time a student spends on an exercise, what percentage of questions are answered correctly, what percentage of the exercise is completed, metacognitive data , and a student "score" which is essentially used in a competitive or "gaming" capacity within LearnSmart™.

Instead of simply exploring the relationship between using LearnSmart™ and student exam scores, this study seeks to exploit the detailed data generated by the program. From looking more closely at LearnSmart™ reports, central research questions were formed surrounding how specific aspects of LearnSmart™ might be influencing student grades.

First hypothesizing that the clearest relationships might be observed through the examination of student usage and performance on one of the major units in introductory biology, this study focuses on student LearnSmart™ data and formal assessment results for a unit on Cellular Respiration. Through statistical analysis of formal assessment scores and LearnSmart™ data, this study aims to examine:

- Relationships between time spent using LearnSmart™ and assessment results.
- Relationships between percent completion of LearnSmart™ activities and assessment results.
- Relationship between LearnSmart™ Metacognitive data and assessment results.

- Relationships between the gaming-style student score generated by LearnSmart™ and assessment results.

Examining relationships between assessment scores and LearnSmart™ use may serve to benefit instructors and, as a result, students as well. Instructors can present their students with statistical evidence that LearnSmart™ is effective and specific information about how to maximize its use. If we found, for instance, a clear relationship between completing a certain percentage of the activities and earning assessment scores of 85% or better, instructors could pass this information along to encourage the use of LearnSmart™.

Instructors could also learn which LearnSmart™ reports will give them accurate representations of overall class performance, and which are better-suited for use in one-on-one meetings with students. The goal of this study is to know more about the effects of the features of LearnSmart™ in order to maximize these features to produce the best student outcomes. As such, based on the results herein, my own teaching and learning experiences, and those of my faculty advisor (Windelspecht, personal communication) this study includes best practices designed to provide helpful advice for the implementation and continued use of adaptive learning technology in the classroom.

MATERIALS AND METHODS

Research Involving Human Subjects

This study was reviewed by Appalachian State University's Office of Student Research Institutional Review Board (IRB) via exemption application under the following exemption category: "Research conducted in established or commonly accepted educational settings, involving normal education practices, such as (a) research on regular and special education instructional strategies, or (b) research on the effectiveness of or the comparison among instructional techniques, curricula, or classroom management methods." On February 28, 2012, the IRB determined the study to be exempt from further review according to the regulatory category cited above under 45 CFR 46.101(b). Any questions regarding this exemption status can be addressed to the IRB via email at irb@appstate.edu. A copy of the IRB exemption notice is included with this document (Appendix A).

Selection of Students and Instructors

In order to minimize issues like consistency of instruction and course content, instead of examining several different courses of introductory biology taught by several different instructors, this study sought out a large section (roughly 200 students) or sections of students in the same course taught by the same, seasoned instructor. As such, a section of an introductory non-majors biology course at a mid-sized southeastern university, which included 193 students, was chosen for this study. The use of LearnSmart™ was available to all students, though it was not a requirement for this course.

Data Collection

Performance data were obtained from the LearnSmart™ system and the ASULearn learning management system used by Appalachian State University. In accordance with the IRB requirements, data provided by the instructor were coded in order to remove all student identifiers prior to analysis. Student names were replaced with research identification numbers, which in no way related to the students' identities.

The following reports were generated from the ASULearn and LearnSmart™ systems. Unless otherwise noted, all data are associated with Chapter 6: How Cells Release Energy, from the course text book, *Biology: Concepts and Investigations*, 3rd edition (Hoefnagels, 2013). All reports were downloaded as .csv files and then converted to Microsoft Excel™ for organization.

LearnSmart Reports

- Performance reports that included: time spent on the Chapter 6 module, the percent of the activity that was completed, and a student score value.
- Metacognitive Analysis. These reports are only generated across all of the content of the course, and were not specific to the Chapter 6 module on cellular respiration. The metacognitive data summarizes students' awareness of their knowledge when completing exercises, broken down into the following four categories:
    - Correct and aware,
    - Correct and unaware,
    - Incorrect and aware, and
    - Incorrect and unaware.

ASULearn Reports

- Performance on an in-class exam ("exam 2")for the course, which included the topic of cellular respiration.
- Performance on an open-book cellular respiration quiz administered online through ASULearn.
- Student responses to a voluntary online "Student LearnSmart™ Usage Survey". The survey questions and student responses can be found in Appendix B.

The raw data were organized from several files into one all-inclusive excel file in order to include all of the aforementioned LearnSmart™ and assessment data onto a single spreadsheet. Data involving time spent on LearnSmart™ activities was converted from hours and minutes (hh:mm) to minutes. Blank entries were left blank. Some records included multiple entries for the same student. In these cases, which resulted from students registering multiple times for the LearnSmart™ material, the data were used from the attempt during which the student spent no less than 1 minute on the material to avoid including data that may have resulted from accidental logout from the program. Complete raw data are available upon request.

Data Analysis

All analyses were performed using JMP 10.0 (SAS Institute Inc.). The vast majority of the data were analyzed using simple linear regression, where assessment scores were treated as the dependent variable, *x*, and LearnSmart™ data were treated as the explanatory variable, *y*. Simple linear regression was chosen because the focus of this study was to determine the best practices methods of utilizing LearnSmart™ in a classroom, and therefore a regression analysis would allow me to assess the amount of variation in assessment scores that is attributed to specific aspects of LearnSmart™.

Statistical Analyses. To determine statistical significance when comparing average assessment scores, t-tests were performed.

In order to interpret how well future outcomes (assessment scores) are likely to be predicted by our experimental linear models, I calculated the coefficient of determination, R^2, which, for the simple linear regression performed in this study, had a possible range from 0 to 1.

In order to determine the statistical significance of the linear relationships observed, I also calculated p-values for each of the data sets analyzed via linear regression.

Comparing Average Assessment Scores. Average exam score with standard deviation and average Chapter 6 quiz score with standard deviation was calculated separately for:

1. All records indicating any LearnSmart™ use,
2. All records indicating no LearnSmart™ use,
3. All records indicating use of LearnSmart™ for the Chapter 6 module,

4. All records indicating no LearnSmart™ use for the Chapter 6 module.

Average exam score with standard deviation was calculated for:

1. All records indicating average use of less than 50% of all LearnSmart™ exercises, and
2. All records indicting average use of 50% or more of all LearnSmart™ exercises.

Average quiz score with standard deviation was calculated for:

1. All records indicating use of less than 50% of the Chapter 6 module, and
2. All records indicating use of 50% or more of the Chapter 6 module.

The results were displayed as column graphs in order to compare average assessment scores based upon:

1. Average assessment scores and overall use or non-use of LearnSmart™,
2. Average assessment scores and use or non-use of LearnSmart™ for the Chapter 6 module, and
3. Two categories of LearnSmart™ percent completion:
    a. Average exam score with average use of less than 50% of all LearnSmart™ exercises or use of 50% or more of all LearnSmart™ exercises, and
    b. Average quiz score and use of less than 50% of Chapter 6 module exercises or use of 50% or more of Chapter 6 module exercises.

Then, t-tests were performed for each column graph.

Linear Regression Analyses. One of the following aspects of LearnSmart™ was plotted against assessment score (exam 2 score and Chapter 6 quiz score separately)

- Time spent on the LearnSmart™ Chapter 6 module: To assess whether there is a relationship between the time students invested in the Chapter 6 module exercises and student performance.

- Percent complete on the LearnSmart™ Chapter 6 module: To assess whether there is a relationship between the amount of the Chapter 6 module material completed and student performance.
- LearnSmart™student standing "score" for the Chapter 6 module: To assess whether the gaming aspect of the LearnSmart system has any relation to student performance.
- The four metacognitive categories: overall percent correct and aware, overall percent correct an unaware, overall percent incorrect and aware, overall percent incorrect and unaware, for all LearnSmart™ exercises: To assess whether there is a relationship between student awareness of knowledge of material and overall performance.
- Average time spent on all LearnSmart™ activities: To assess whether there is a relationship between the total time students invested in all of the LearnSmart™ activities and student performance on exam 2 and the Chapter 6 quiz.
- Average percent completion of all LearnSmart™ activities: To assess whether there is a relationship between the total percentage of activities students completed in LearnSmart™ and student performance on exam 2 and the Chapter 6 quiz.

Then, p-values were calculated for each of the linear regression models.

In total, four sets of data were analyzed:

- Data set one compared average exam 2 score and average Chapter 6 quiz score based upon use or non-use of LearnSmart™(n=193), average exam 2 score and average Chapter 6 quiz score based upon use or non-use of LearnSmart™ for the Chapter 6 module (n=193), and average assessment scores based upon an average percent completion threshold of 50(n=193), yielding 6 column graphs.
- Data set two plotted each of the categories of LearnSmart™ data against exam 2 score, and then against Chapter 6 quiz score, yielding 18 linear regressions (n=193).

- Data set three plotted each of the categories of LearnSmart ™ against exam 2 score, except that these analyses were performed on a revised data set, excluding students that did not use LearnSmart™ at all, yielding 9 linear regressions (n = 60). This analysis was performed in order to exclude some of the “0” data points seen in Data Set 2.
- Data set four plotted each of the categories of LearnSmart ™ against Chapter 6 quiz score, except that these analyses were performed on a revised data set, excluding students that did not use LearnSmart™ for the Chapter 6 module (n = 28), yielding 9 linear regressions. This analysis was performed in order to exclude some of the “0” data points seen in Data Set 2.
- Data set five plotted time spent on LearnSmart™ activities against each of the assessment scores for the revised data sets after removing the sample outliers (sample minimum and maximum), resulting in four linear regressions. Total time spent on all LearnSmart™ activities was plotted versus exam 2 score (n = 58). Time spend on the Chapter 6 module was plotted versus Chapter 5 quiz score (n = 26).

  Outliers were removed for time data only due to a few suspicious time values. The maximum total time value was 1278 minutes, while the next highest value was less than half this, at 637 minutes. As such, I decided to remove outliers to see if the data was skewed.

RESULTS

Comparing Average Assessment Scores

Data Set One (n = 193). The following figures compare average assessment score based on overall use or non-use of LearnSmart™, use or non-use of LearnSmart™ for the Chapter 6 module, and overall use of LearnSmart™ for less than 50% of exercises or 50% or more of exercises. All exam scores are out of 100 points and all quiz scores are out of 60 points.

Figures 4 and 5 compare average exam 2 score based on overall LearnSmart™ use or non-use. The average exam score was 81.08 ± 11.86 for LearnSmart™ users and 80.18 ± 13.07 for non-users. Figure 5 compares average quiz score based on overall LearnSmart™ use or non-use. The average quiz score was 86.33 ± 9.74 for LearnSmart™ users and 84.71 ± 14.54 for non-users.

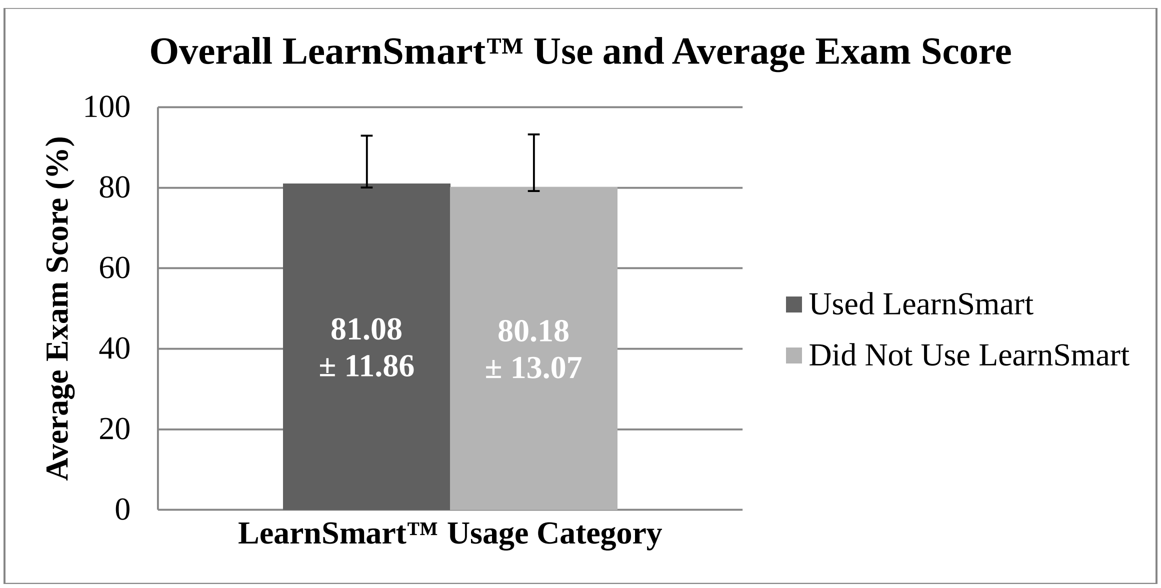

Figure 4. Average exam grade with standard deviation based on LearnSmart™ usage category. Values are based on 100 points ($p > 0.50$).

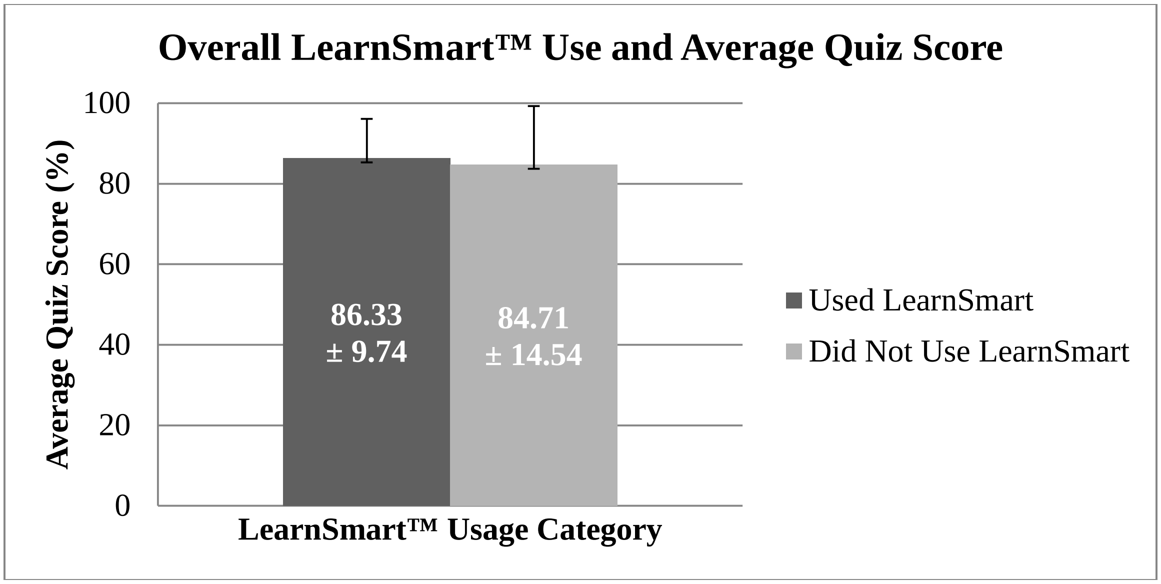

Figure 5. Average quiz grade with standard deviation based on LearnSmart™ usage category Values are based on percent of 60 possible points on the quiz ($p > 0.40$).

The next pair of figures, 6 and 7, compares average exam score and average quiz score, respectively, based upon use or non-use of LearnSmart™ for the Chapter 6 module. The average exam grade was 81.64 ± 11.98 for Chapter 6 module users and 80.38 ± 12.25 for non-users. The average quiz grade was 87.5 ± 8.49 for Chapter 6 module users and 84.59 ± 10.75 for non-users.

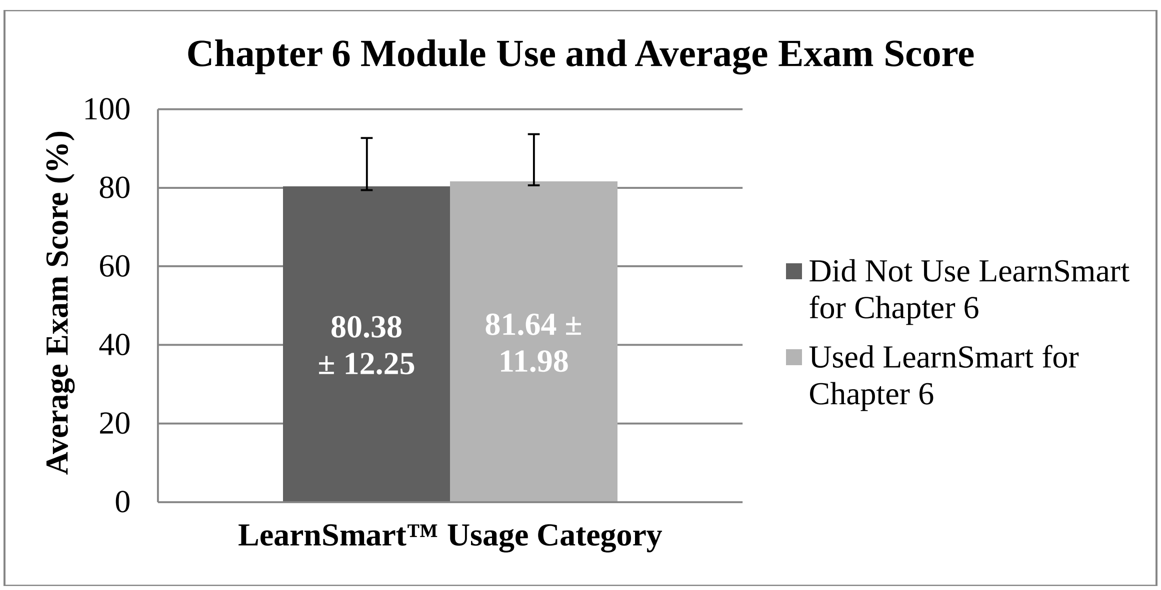

Figure 6. Average exam score with standard deviation based on Chapter 6 LearnSmart™ usage category. Values are based on 100 possible points ($p > 0.50$).

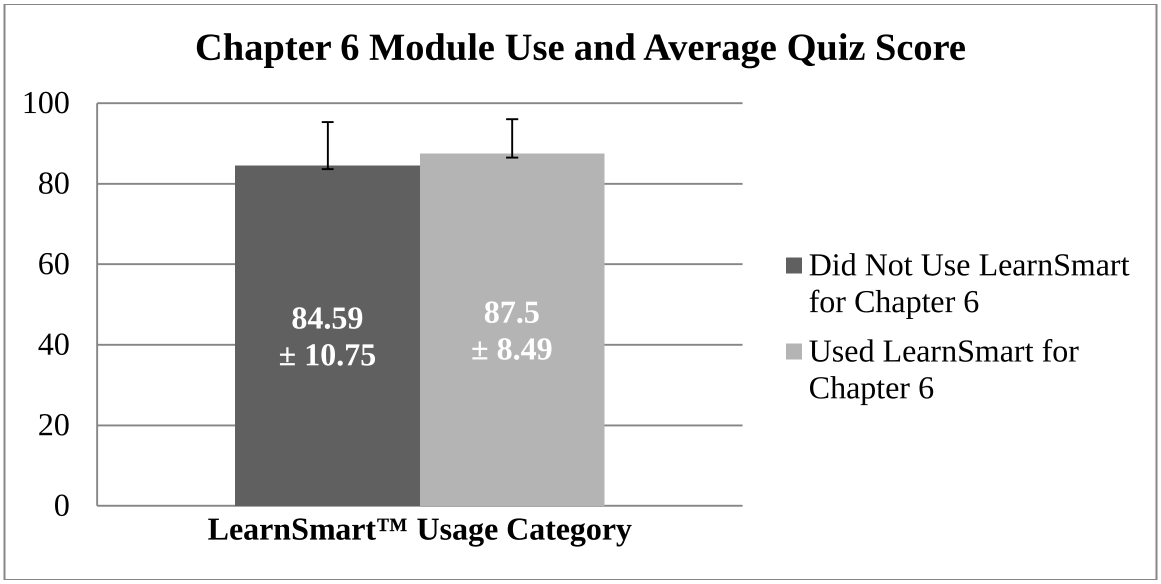

Figure 7. Average quiz score with standard deviation based on Chapter 6 LearnSmart™ usage category. Values are based on percent of 60 possible points on the quiz ($p > 0.20$).

Figures 8 and 9 compare average exam score based on average percent completion of all LearnSmart™ exercises and average Chapter 6 quiz score based on percent completion of the Chapter 6 module. The average exam score was79.86 ± 11.90 for students who completed an average of less than 50% of all LearnSmart™ exercises before the exam, compared to average exam score of 90.73 ± 7.91 for students who completed an average of 50% or more of all LearnSmart™ exercises before the exam. Figure 9 compares average Chapter 6 quiz score based on percent completion of the Chapter 6 LearnSmart™ module. The average quiz score was 84.78 ± 13.58 for students who used less than 50% of the Chapter 6 LearnSmart™ module, compared to an average quiz score of 89.84± 7.86 for students who used 50% or more of the Chapter 6 LearnSmart™ module.

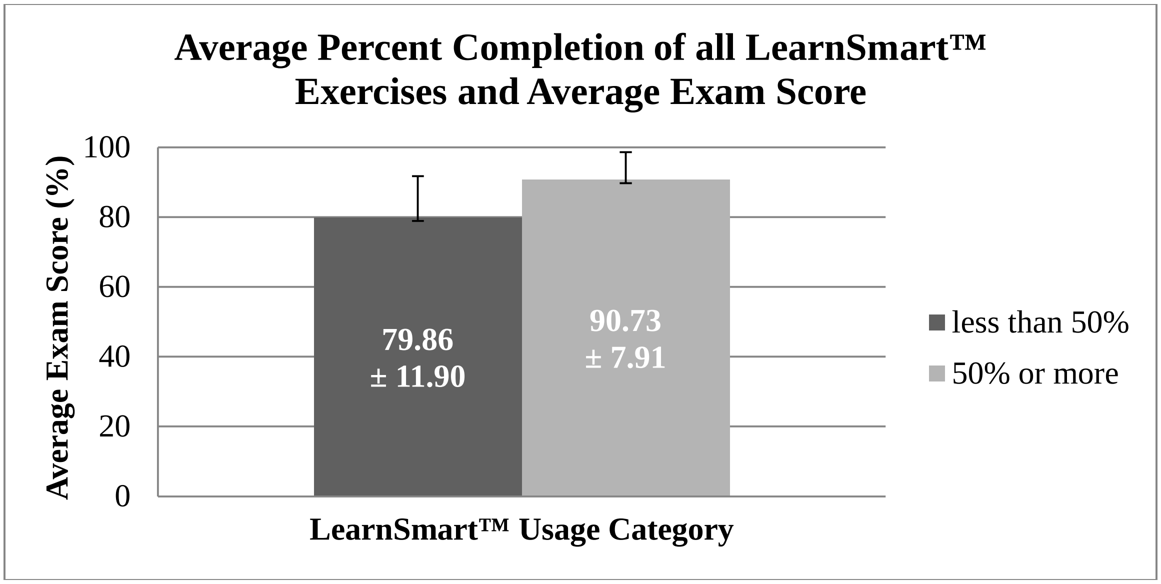

Figure 8. Average exam score with standard deviation based on average completion of less than 50% or 50% or more of LearnSmart™ exercises ($p > 0.50$).

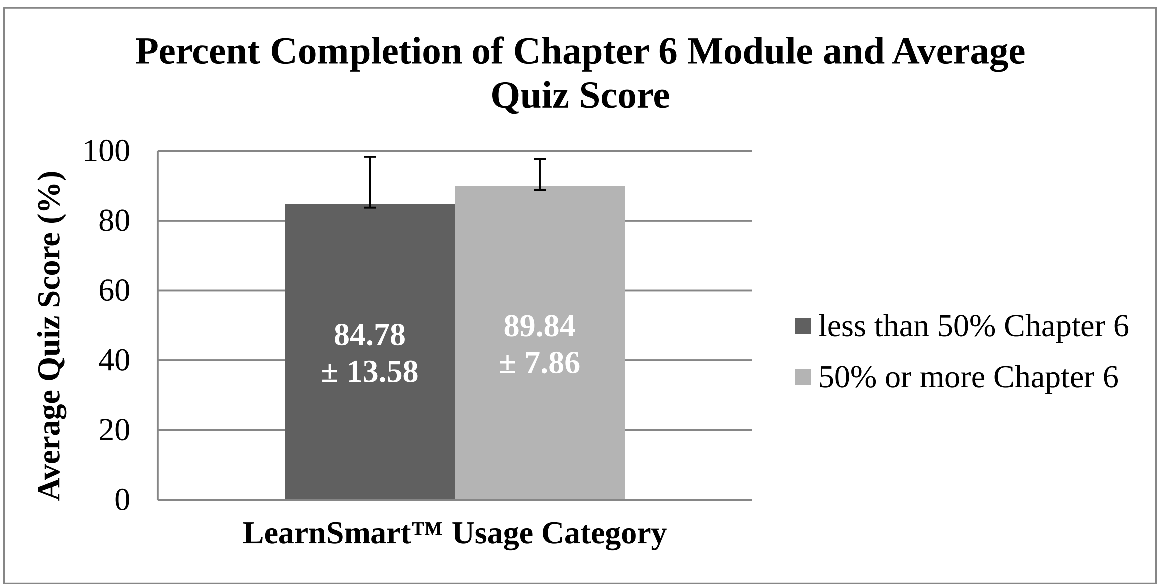

Figure 9. Average quiz score with standard deviation based on completion of less than 50% or 50% or more of LearnSmart™ exercises ($p > 0.50$).

Linear Regression Analyses

Data Set 2 (n=193). The following figures are linear regression analyses of LearnSmart™ data versus student exam scores. All exam scores are out of 100 points.

Figures 10- 12 explore possible linear relationships between LearnSmart™ Chapter 6 module student score and student exam score, Chapter 6 module time and student exam score, and Chapter 6 module percent completion and student exam score, respectively.

The R^2 value was 0.152 for the linear model of Chapter 6 module student score versus exam score is, 0.0088 for the linear model of Chapter 6 module time versus exam score, and 0.017 for the linear model of Chapter 6 module percent completion versus exam score.

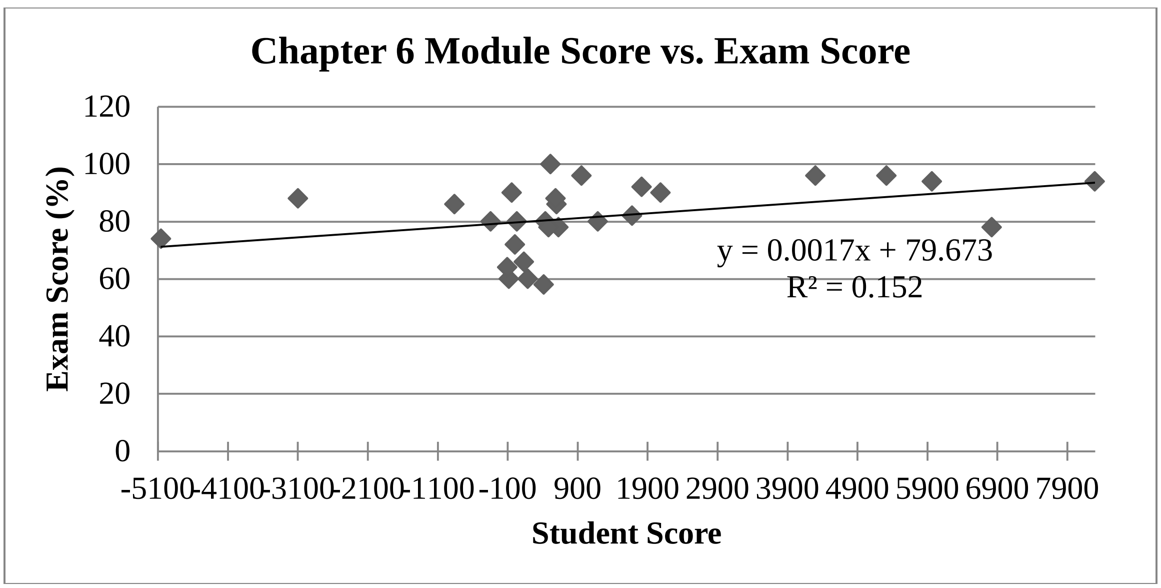

Figure 10. LearnSmart™-generated Chapter 6 module student score versus student exam score ($p < 0.05$).

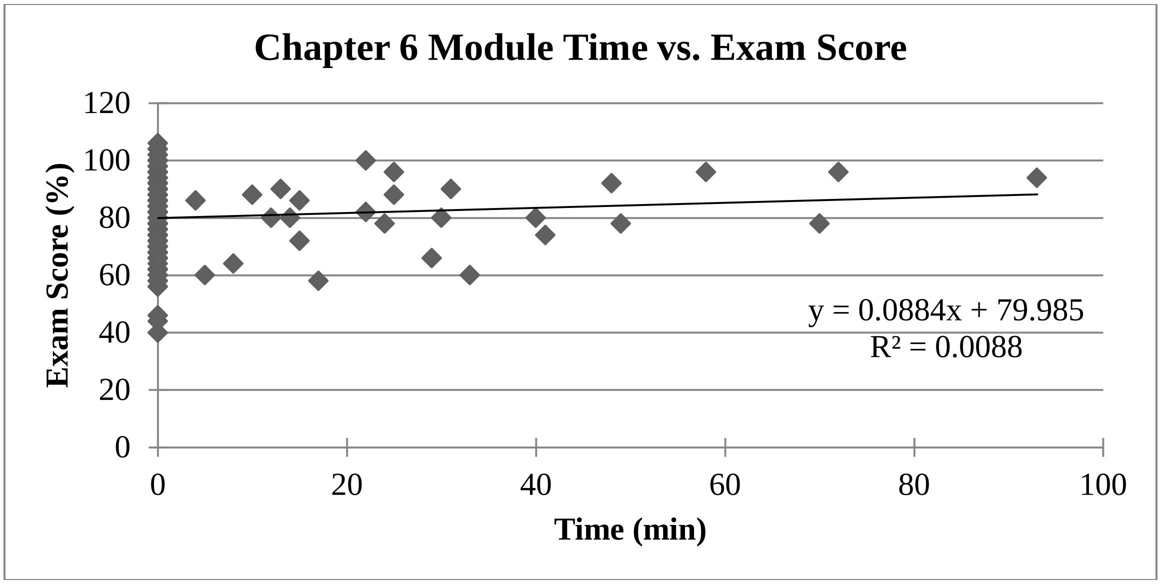

Figure 11. Time spent on LearnSmart™ cellular respiration model versus student exam score ($p > 0.10$).

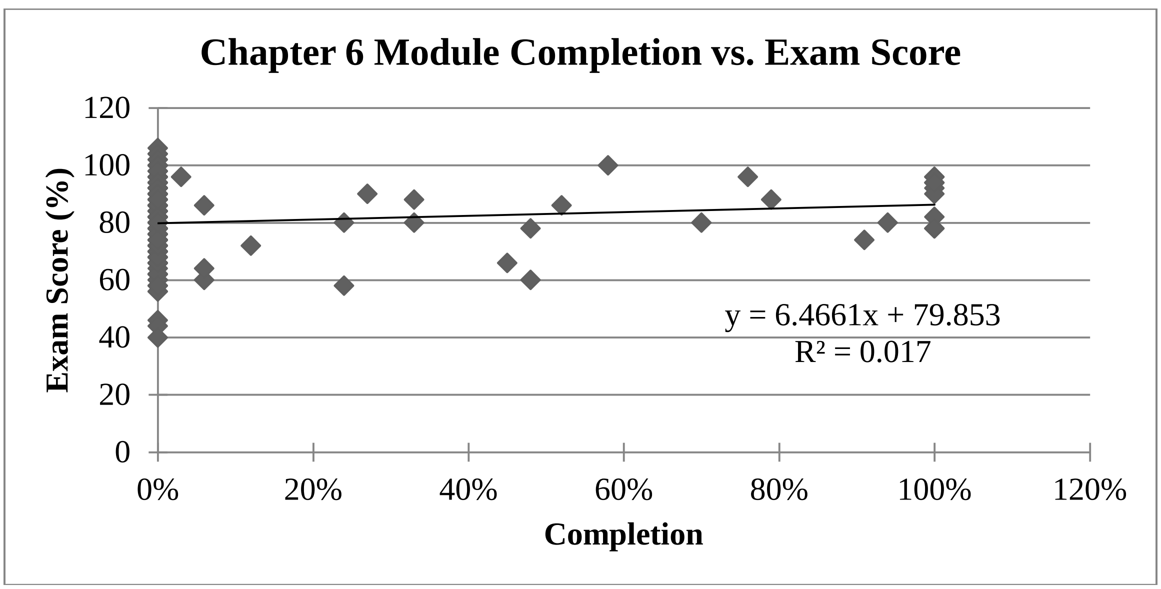

Figure 12. Percent completion of LearnSmart™ cellular respiration module versus student exam score ($p < 0.10$).

Figures 13-15 explore linear relationships between the four categories of metacognitive data and student exam score. The R^2 value was 0.003 for the linear model of metacognitive: correct and aware versus exam score, 0.0127 for the linear model of metacognitive: correct and unaware versus exam score, $3e^{-8}$ for the linear model of metacognitive: incorrect and aware versus exam score, and 0.002 for the linear model of metacognitive: incorrect and unaware versus exam score.

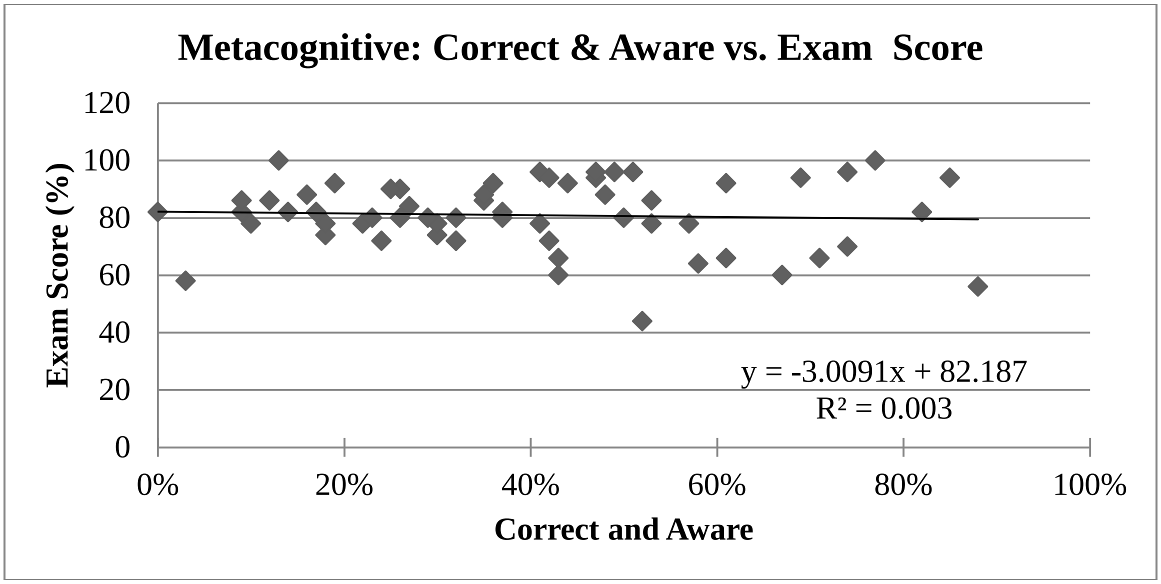

Figure 13. LearnSmart™ Metacognitive data (percent of questions answered correctly in cases where students selected that they were confident that they knew the correct answer) versus student exam score ($p > 0.50$).

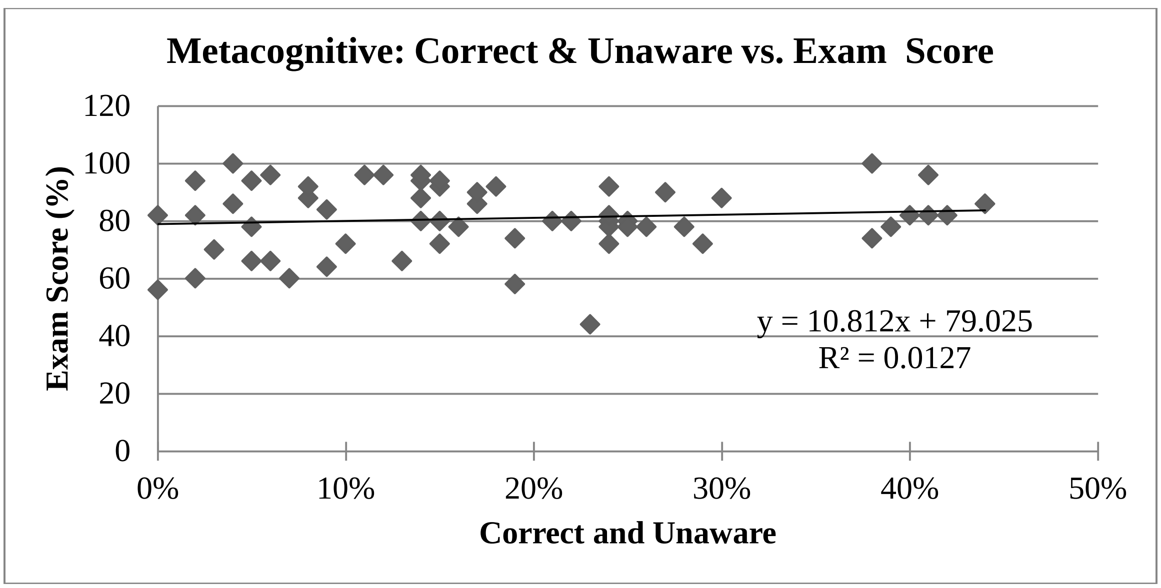

Figure 14. LearnSmart™ Metacognitive data (percent of questions answered correctly in cases where students selected that they were not confident that they knew the correct answer) versus student exam score ($p > 0.20$).

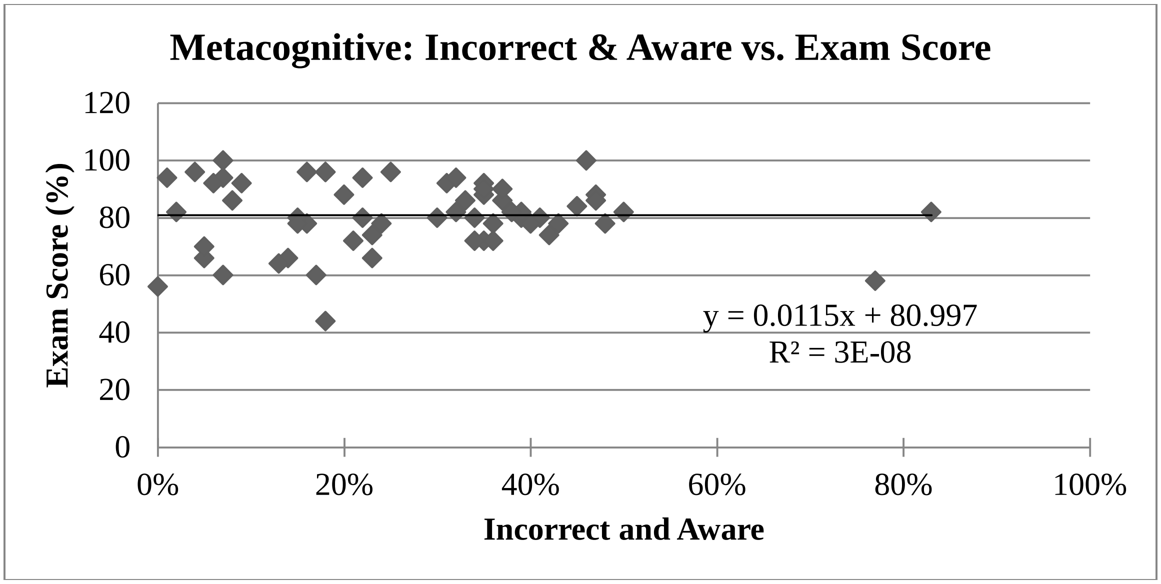

Figure 15. LearnSmart™ Metacognitive data (percent of questions answered incorrectly in cases where students selected that they were guessing -were confident that they did not know the correct answer) versus student exam score ($p > 0.50$).

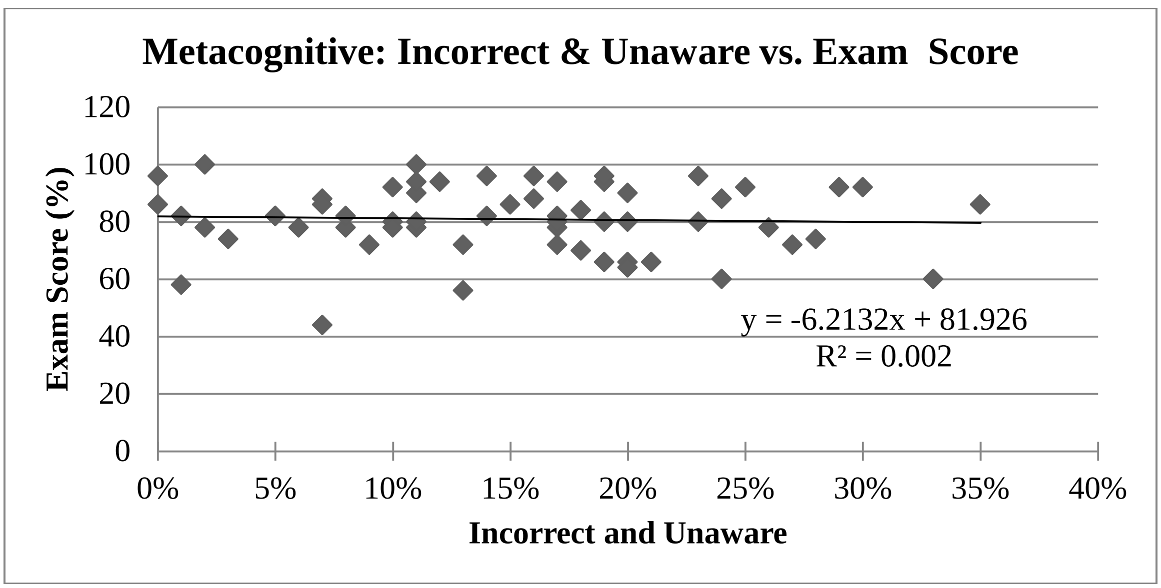

Figure 16. LearnSmart™ Metacognitive data (percent of questions answered incorrectly in cases where students thought that they knew the correct answer) versus student exam score ($p >0.50$).

Figure 17 examines the linear relationship between total time spent using LearnSmart™ and student exam score. Figure 18 explores a possible linear relationship between total percent completion of all LearnSmart™ exercises and student exam score.

The R^2 value was 0.0171for the linear model of total time spent on LearnSmart™ exercises versus exam score and 0.0395 for the linear model of total percent completion of all LearnSmart™ exercises and exam score.

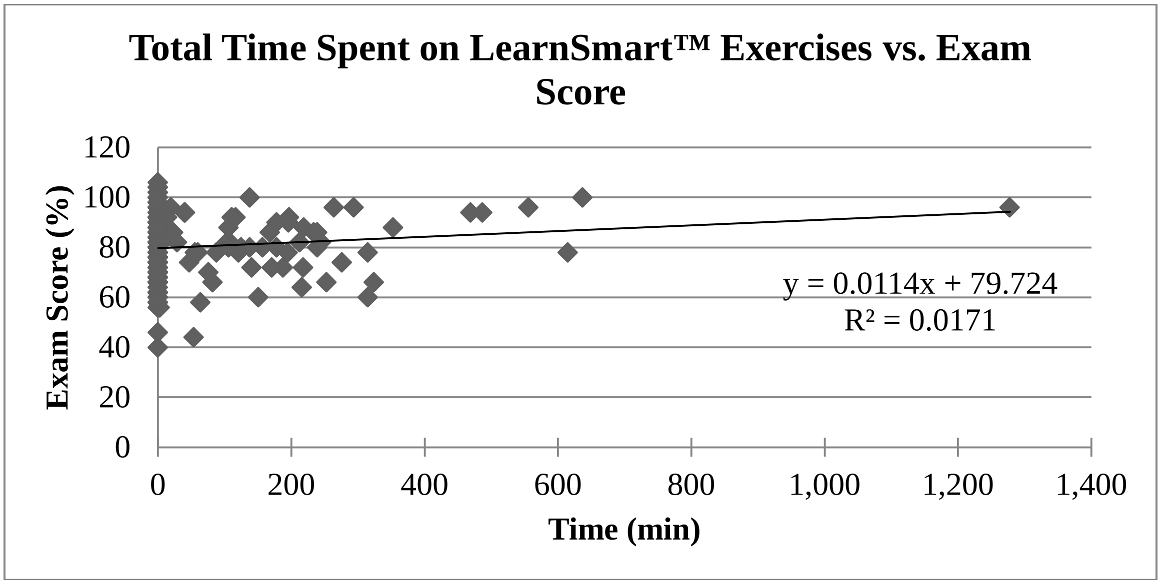

Figure 17. Total spent on all LearnSmart™ exercises (including the cellular respiration module) versus student exam score ($p < 0.10$).

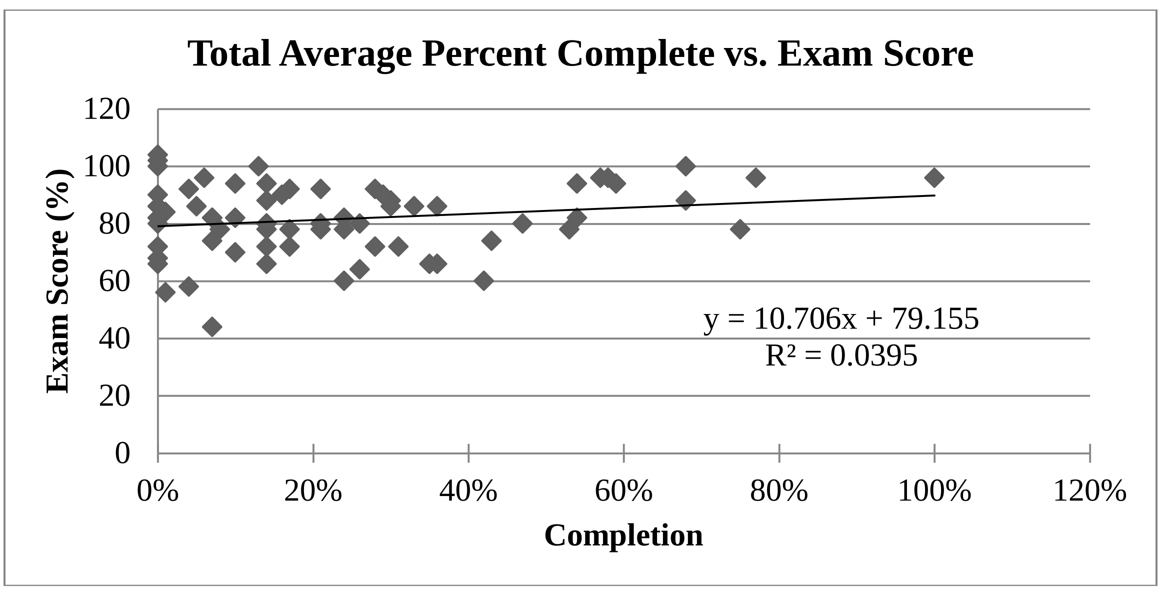

Figure 18. Average percent completion of all LearnSmart™ exercises (including the cellular respiration module) versus student exam score ($p < 0.10$).

The following figures are linear regression analyses of LearnSmart™ data versus student Chapter 6 quiz scores. All quiz scores are out of 60 points.

Figures 19-21 explore linear relationships between LearnSmart™ Chapter 6 module student score and Chapter 6 quiz score, Chapter 6 module time and Chapter 6 quiz score, and Chapter 6 module percent completion and Chapter 6 quiz score, respectively. The R^2 value was 0.025 for the linear model of Chapter 6 module score and Chapter 6 quiz score, 0.0068 for the linear model of Chapter 6 module time and Chapter 6 quiz score, and 0.0055 for Chapter 6 module completion and Chapter 6 quiz score.

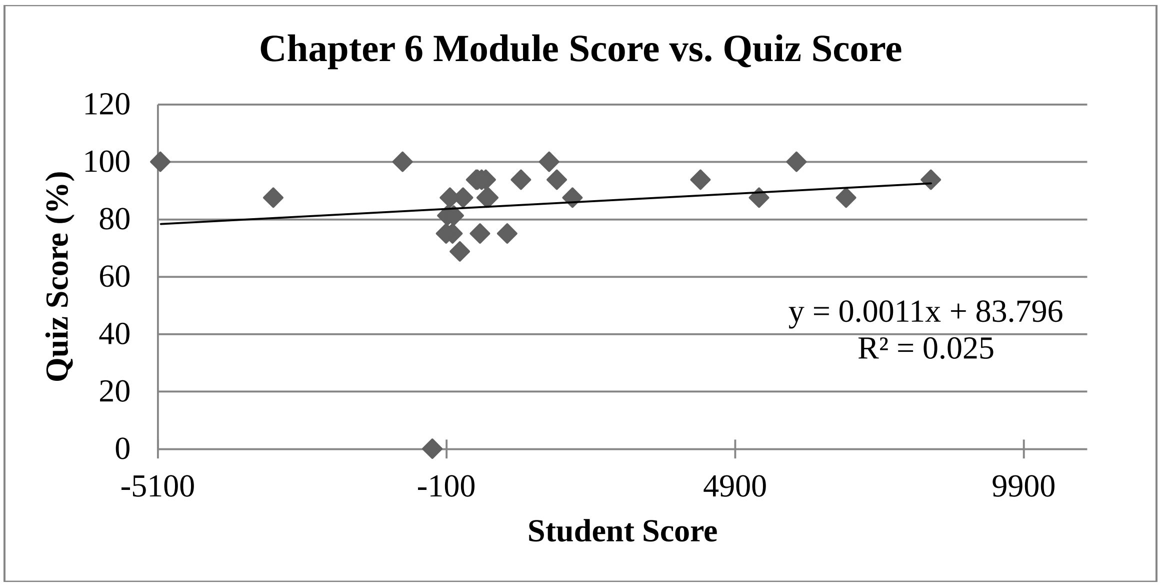

Figure 19. LearnSmart™-generated student score versus student Chapter 6 quiz score ($p > 0.20$).

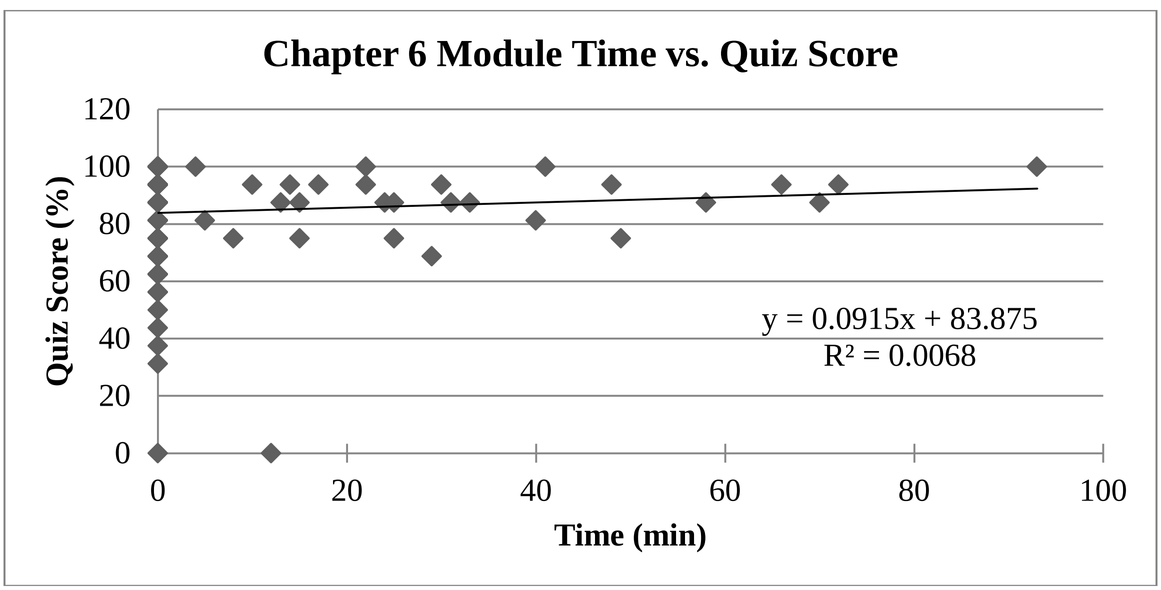

Figure 20. Time spent on LearnSmart™ cellular respiration module versus student Chapter 6 quiz score ($p < 0.20$).

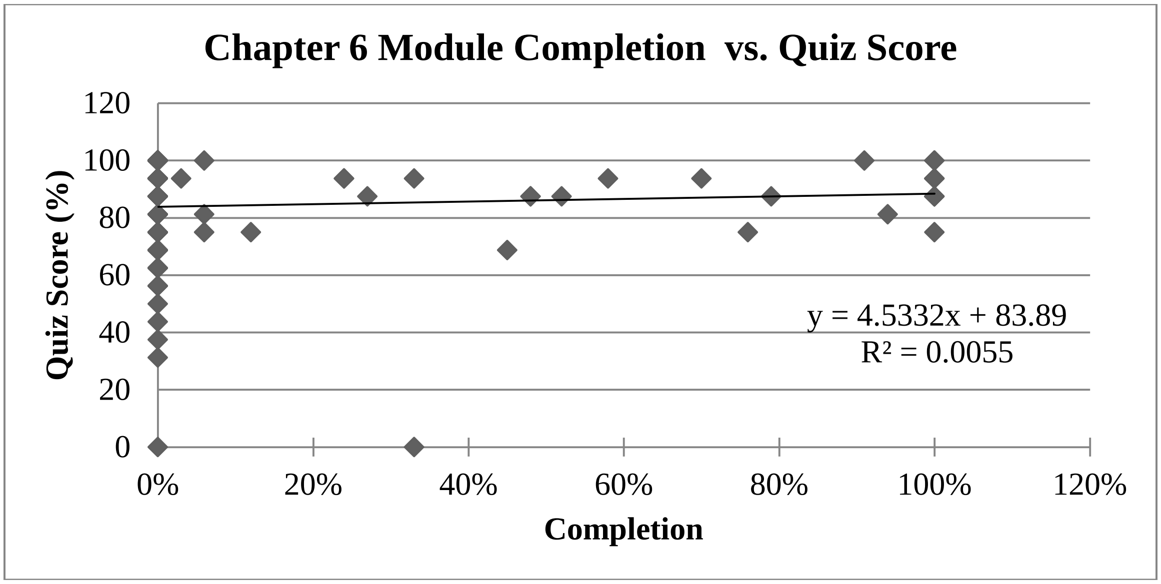

Figure 21. Percent completion of LearnSmart™ cellular respiration module versus student Chapter 6 quiz score ($p < 0.20$).

Figures 22-25 explore linear relationships between the four categories of metacognitive data and student Chapter 6 quiz score. The R^2 value was 0.0009 for the linear model of metacognitive: correct and aware versus quiz score, 0.0007 for the linear model of metacognitive: correct and unaware versus quiz score, 0.0007 for the linear model of metacognitive: incorrect and aware, and 0.0005 for the linear model of metacognitive: incorrect and unaware.

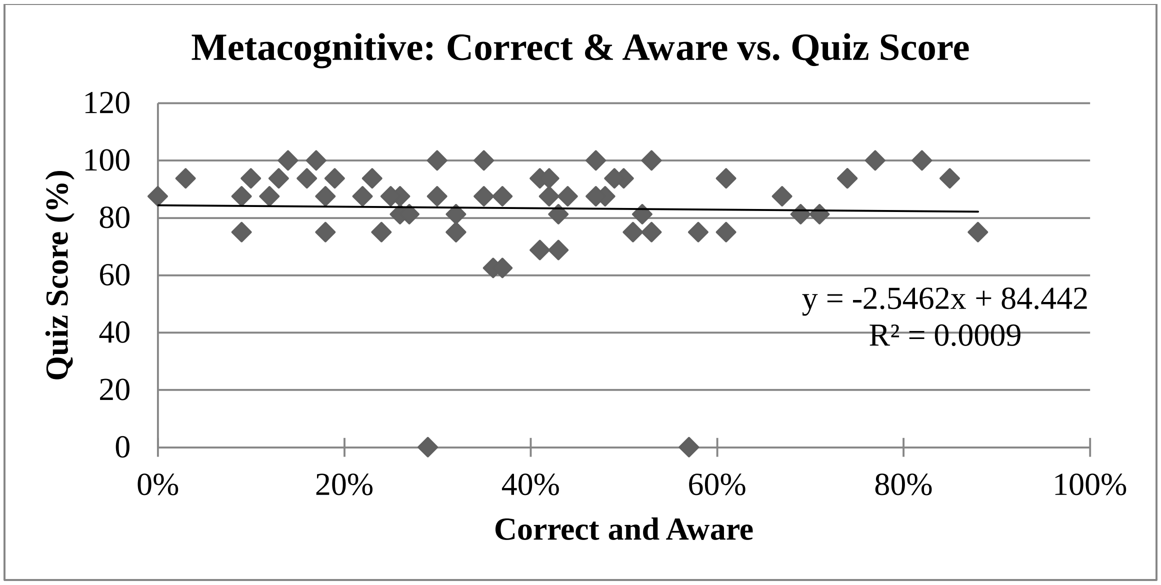

Figure 22. LearnSmart™ Metacognitive data (percent of questions answered correctly in cases where students selected that they were confident that they knew the correct answer) versus student Chapter 6 quiz score (p> 0.50).

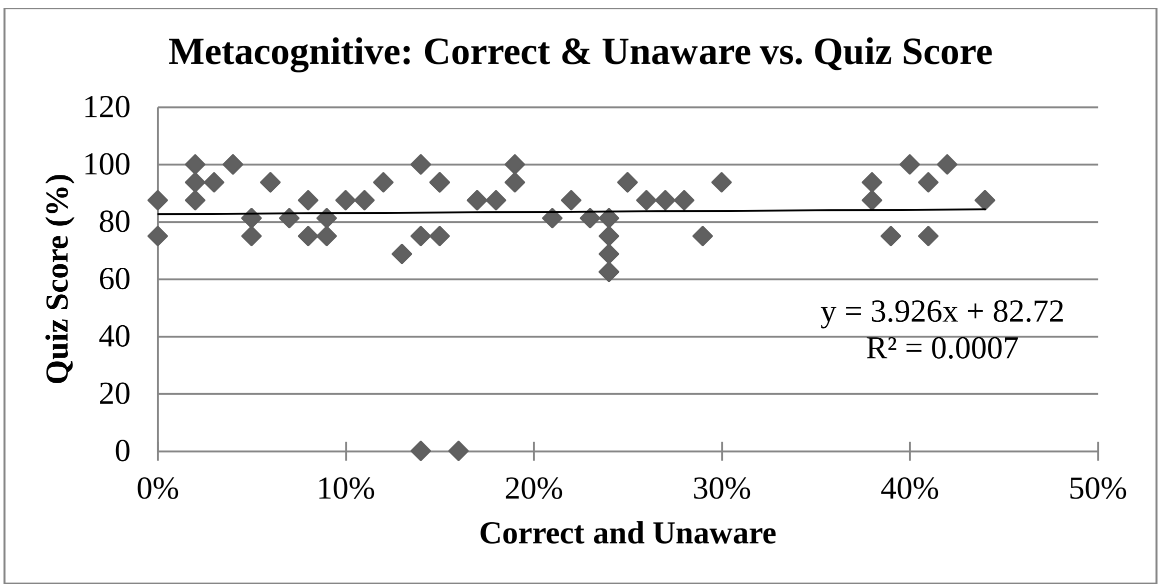

Figure 23. LearnSmart™ Metacognitive data (percent of questions answered correctly in cases where students selected that they were not confident that they knew the correct answer) versus student Chapter 6 quiz score (p> 0.50).

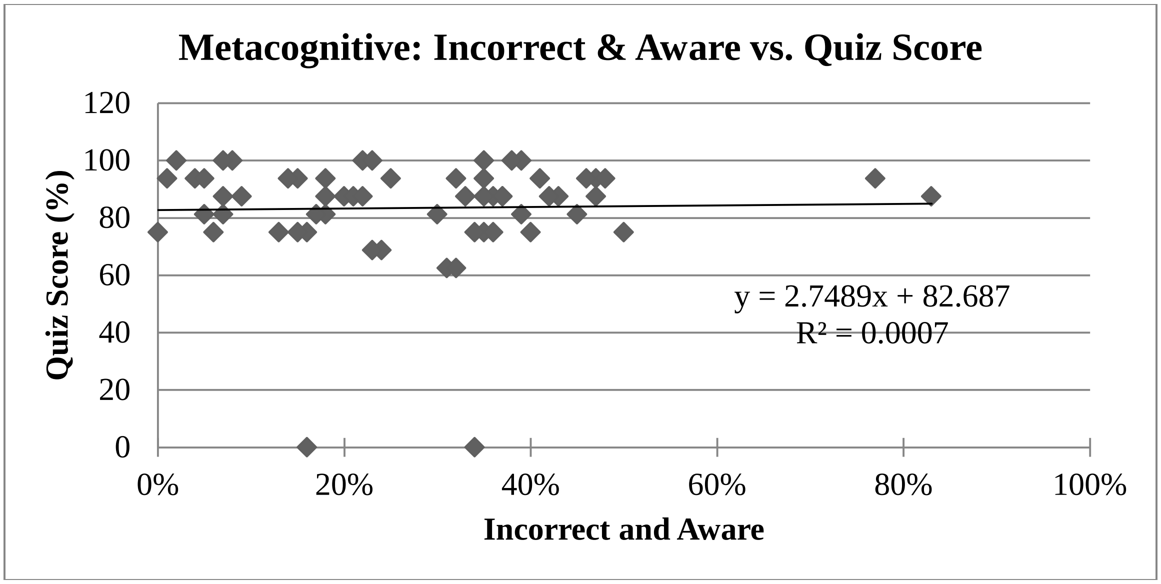

Figure 24. LearnSmart™ Metacognitive data (percent of questions answered incorrectly in cases where students selected that they were guessing -were confident that they did not know the correct answer) versus student Chapter 6 quiz score ($p > 0.50$).

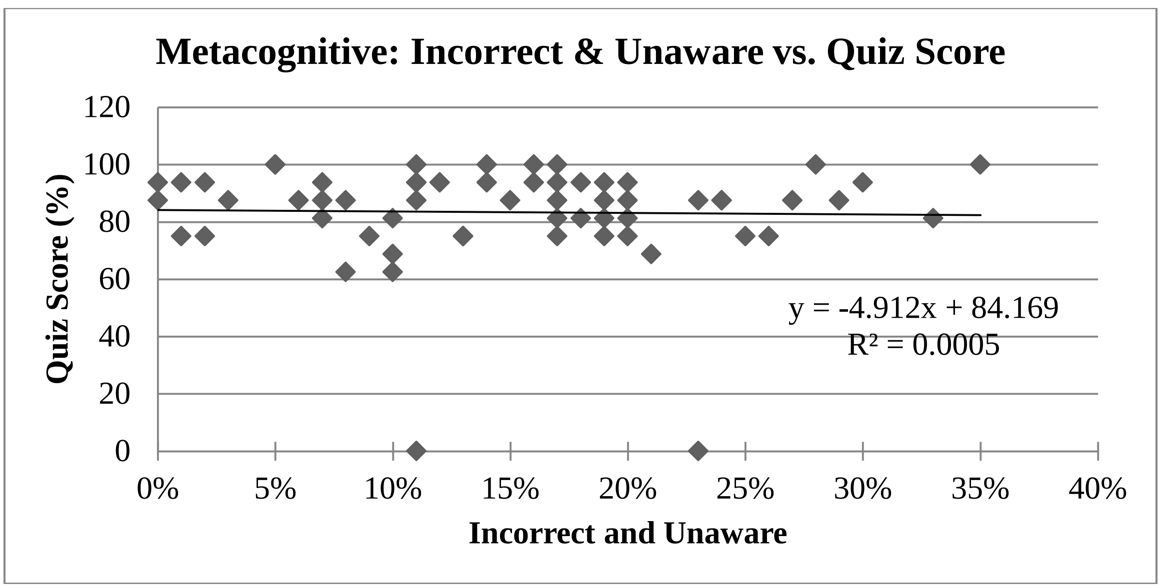

Figure 25. LearnSmart™ Metacognitive data (percent of questions answered incorrectly in cases where students thought that they knew the correct answer) versus student Chapter 6 quiz score ($p > 0.50$).

Figure 26 examines the linear relationship between total time spent using LearnSmart™ and Chapter 6 quiz score. Figure 27 explores the linear relationship between total percent completion of all LearnSmart™ exercises and Chapter 6 quiz score. The R^2 value was 0.0034 for the linear model of total time spent on LearnSmart™ exercises versus Chapter 6 quiz score and 0.0046 for the linear model of average total percent completion of all LearnSmart™ exercises.

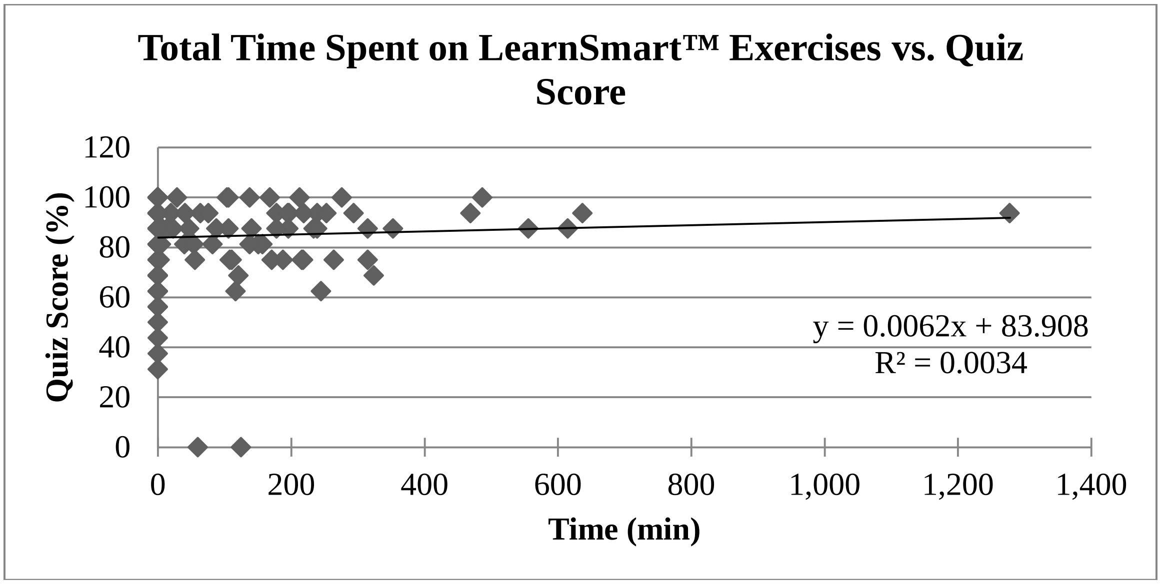

Figure 26. Total time spent on all LearnSmart™ exercises (including the cellular respiration module) versus student Chapter 6 quiz score ($p > 0.20$).

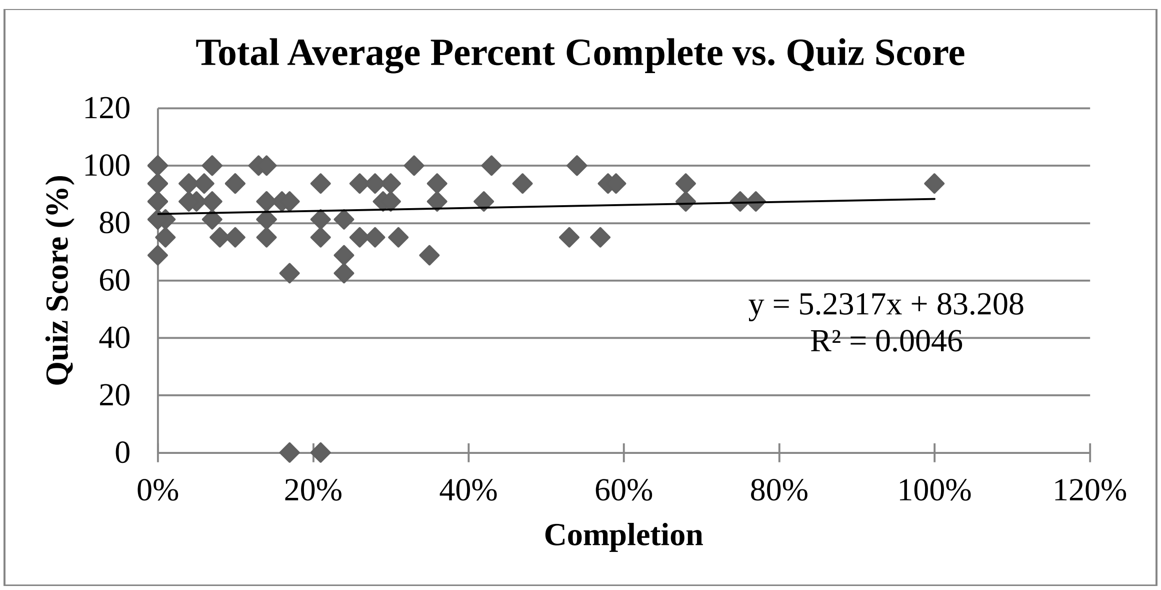

Figure 27. Average percent completion of all LearnSmart™ exercises (including the cellular respiration module) versus student Chapter 6 quiz score ($p > 0.50$).

Data Set 3 (n = 60): The following figures plot LearnSmart™ data against exam 2 data for a revised data set of 60, excluding students who did not use LearnSmart at all. Exam scores are out of 100 points.

Figures 28-30 explore linear relationships between LearnSmart™ Chapter 6 module student score and student exam score, Chapter 6 module time and student exam score, and Chapter 6 module percent completion and student exam score, respectively. The R^2 value was 0.152 for the linear model of student score versus student exam score, 0.0467 for the linear model of time spent on the Chapter 6 module versus exam score, and 0.0665 for the linear model of Chapter 6 module completion versus exam score.

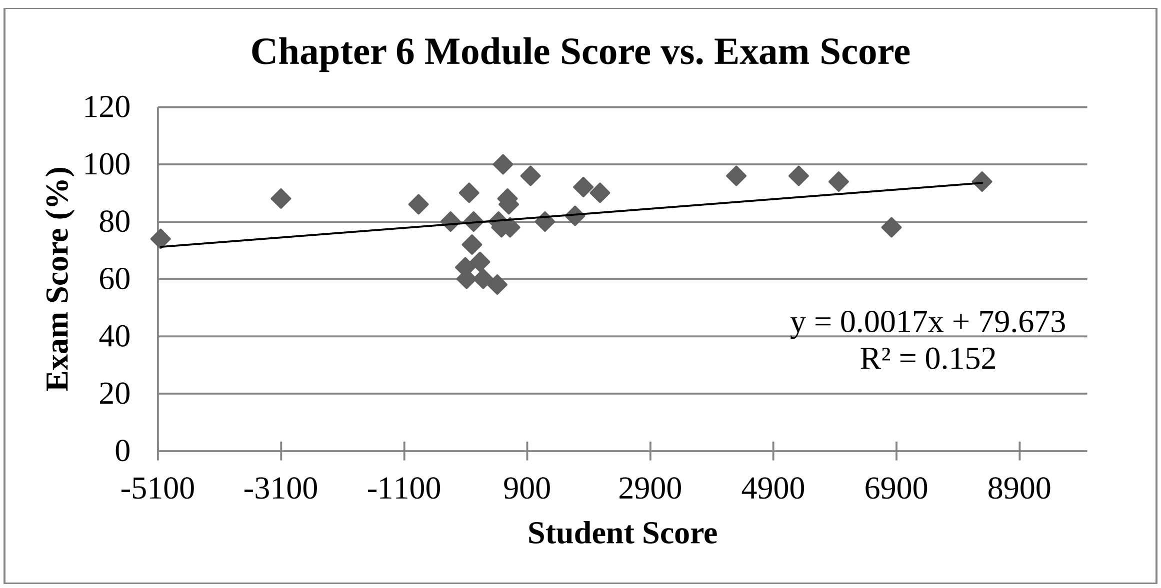

Figure 28. LearnSmart™ -generated student score versus student exam score, excluding students who did not use LearnSmart™ at all ($p < 0.05$).

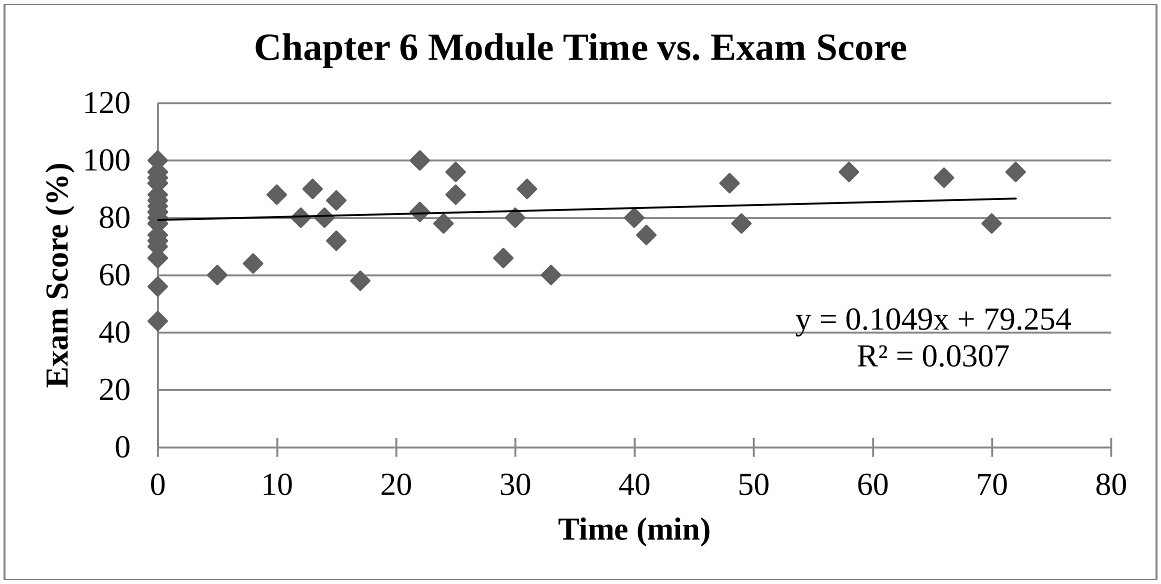

Figure 29. Time spent on LearnSmart™ cellular respiration module versus student exam score, excluding students who did not use LearnSmart™ at all ($p < 0.10$).

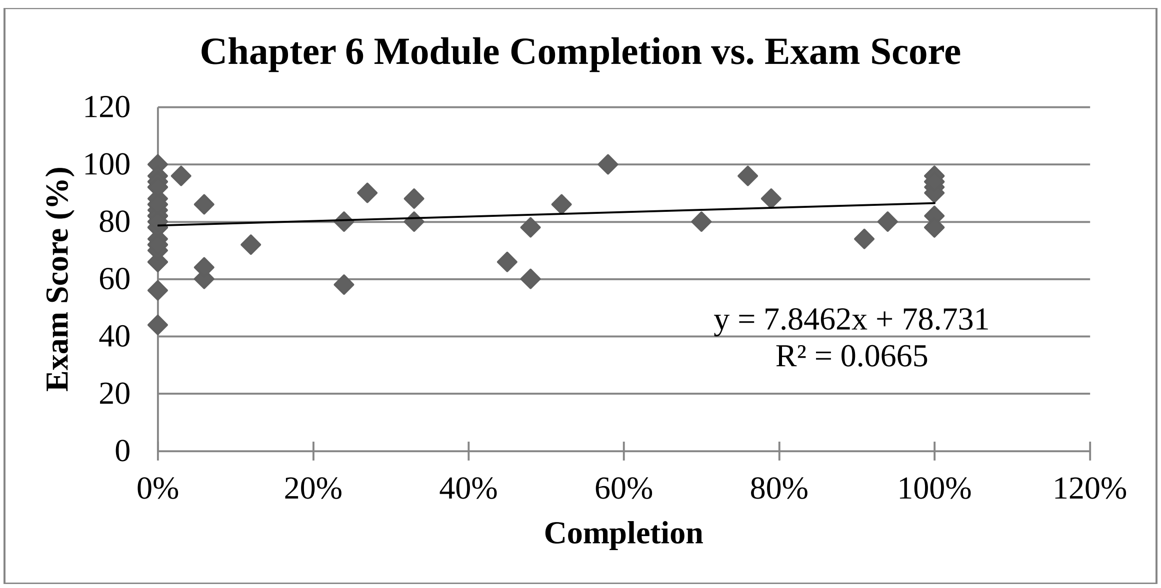

Figure 30. Percent completion of LearnSmart™ cellular respiration module versus student exam score, excluding students who did not use LearnSmart™ at all ($p < 0.05$).

Figures 31-34 explore linear relationships between the four categories of metacognitive data and student exam score. The R^2 value was 0.003 for the linear model of metacognitive: correct and aware versus exam score, 0.0127 for the linear model of metacognitive: correct and unaware versus exam score, $3e^{-8}$ for the linear model of metacognitive: incorrect and aware versus exam score, and 0.002 for the linear model of metacognitive: incorrect and unaware versus exam score.

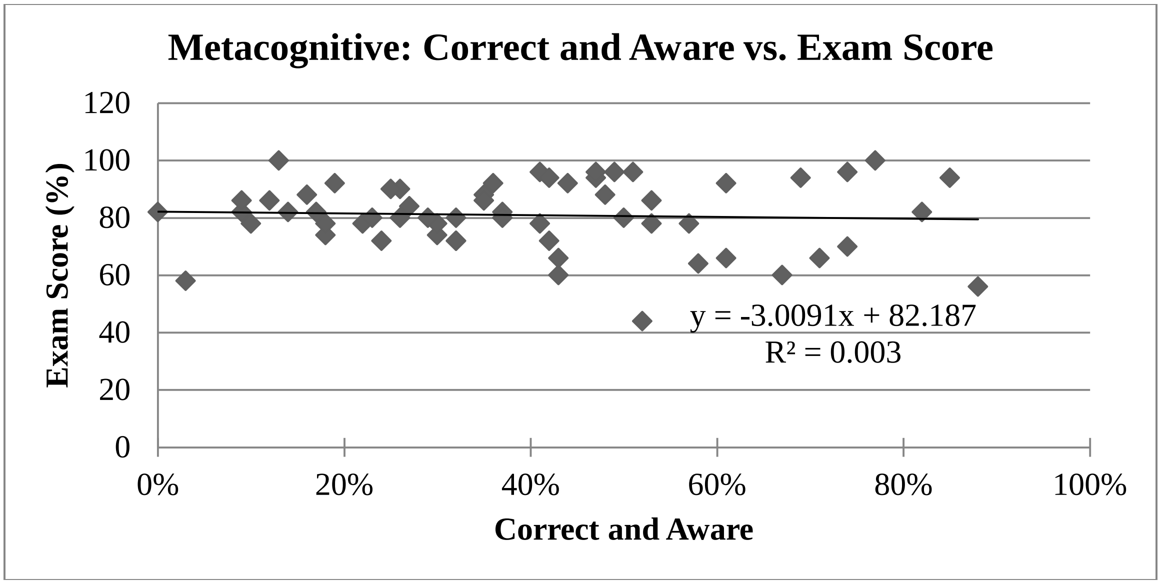

Figure 31. LearnSmart™ Metacognitive data (percent of questions answered correctly in cases where students selected that they were confident that they knew the correct answer) versus student exam score, excluding students who did not use LearnSmart™ for Chapter 6 ($p > 0.50$).

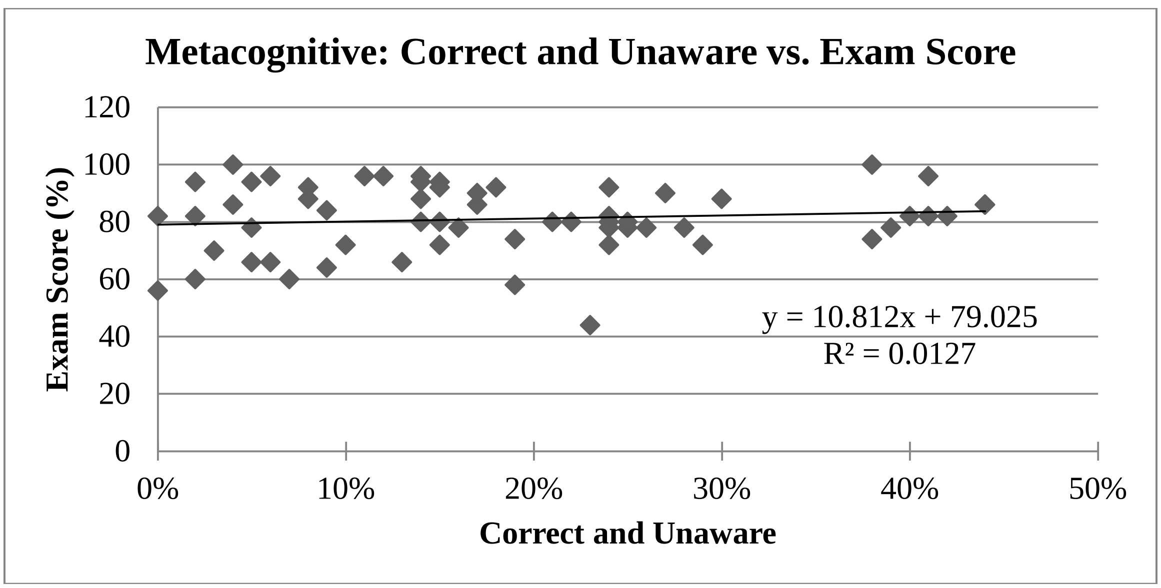

Figure 32. LearnSmart™ Metacognitive data (percent of questions answered correctly in cases where students selected that they were not confident that they knew the correct answer) versus student exam score, excluding students who did not use LearnSmart™ for Chapter 6($p > 0.20$).

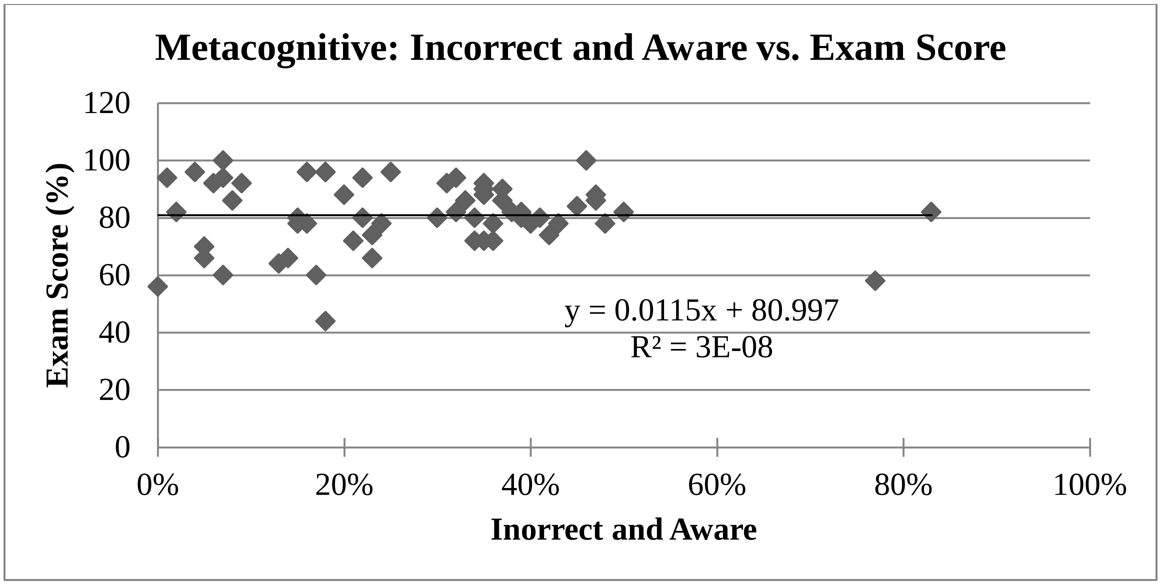

Figure 33. LearnSmart™ Metacognitive data (percent of questions answered incorrectly in cases where students selected that they were guessing-were confident that they did not know the correct answer) versus student exam score, excluding students who did not use LearnSmart™ for Chapter 6(p > 0.50).

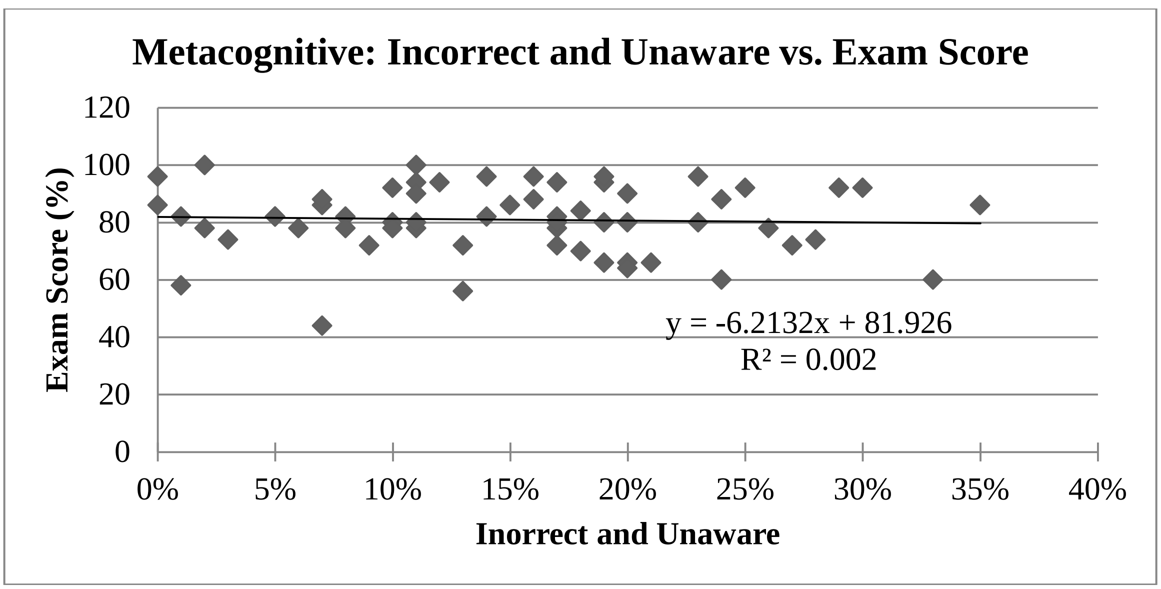

Figure 34. LearnSmart™ Metacognitive data (percent of questions answered incorrectly in cases where students thought that they knew the correct answer) versus student exam score, excluding students who did not use LearnSmart™ for Chapter 6 ($p > 0.50$).

Figure 35 examines the linear relationship between total time spent using LearnSmart™ and student exam score. Figure 36 explores the linear relationship between average total percent completion of all LearnSmart™ exercises and student exam score. The R^2 value was 0.0772 for the linear model of total time spent on LearnSmart™ exercises versus exam score and 0.0978 for the linear model of average total percent completion of LearnSmart™ exercises versus exam score.

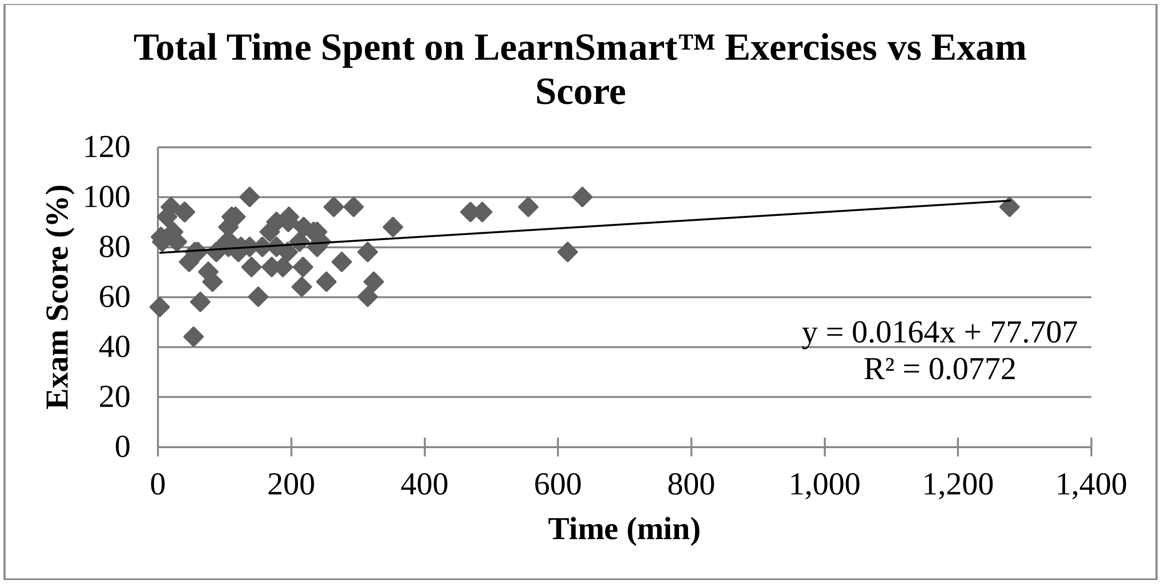

Figure 35. Time spent on all LearnSmart™ exercises (including the cellular respiration module) versus student exam score, excluding students who did not use LearnSmart™ for Chapter 6($p < 0.05$).

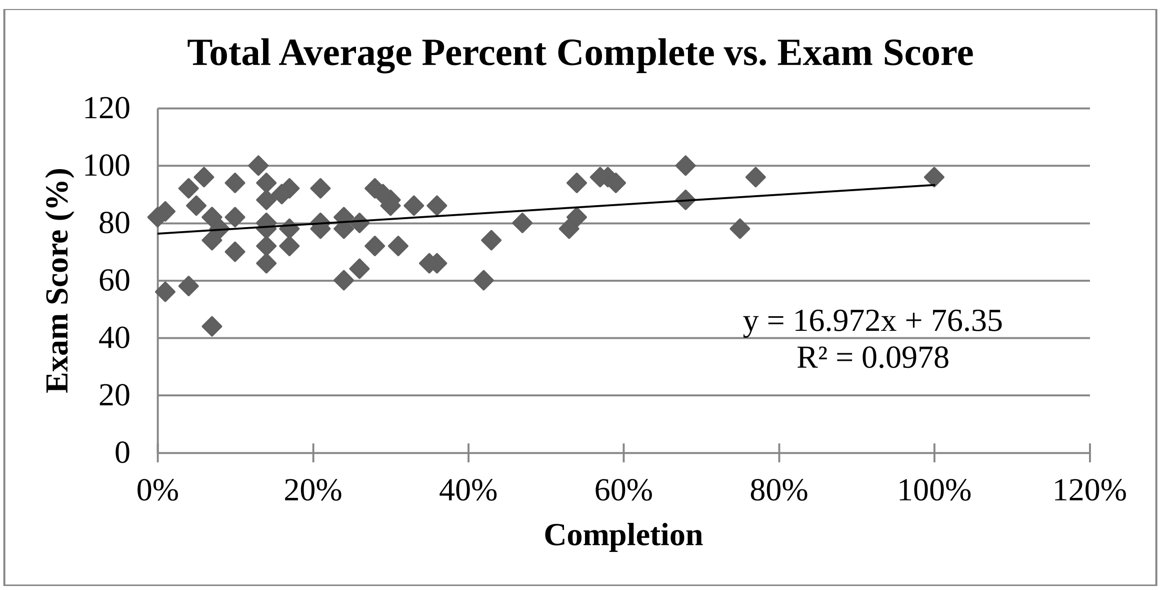

Figure 36. Average percent completion of all LearnSmart™ exercises (including the cellular respiration module) versus student exam score, excluding students who did not use LearnSmart™ for Chapter 6 ($p < 0.05$).

Data Set Four (n=28): The following figures are linear regression analyses of revised data, or student LearnSmart™ data versus student Chapter 6 quiz score for 28 records reflecting LearnSmart™ use for Chapter 6 materials. Quiz score are out of 60 points.

Figures 37-39 explore possible linear relationships between LearnSmart™ Chapter 6 module score and Chapter 6 quiz score, Chapter 6 module time and Chapter 6 quiz score, and Chapter 6 module percent completion and Chapter 6 quiz score, respectively. The R^2 value was 0.025 for the linear model of student score versus Chapter 6 quiz score, 0.0604 for the linear model of time spent on the Chapter 6 module versus Chapter 6 quiz score, and 0.0593 for the linear model of percent completion of the Chapter 6 module versus Chapter 6 quiz score.

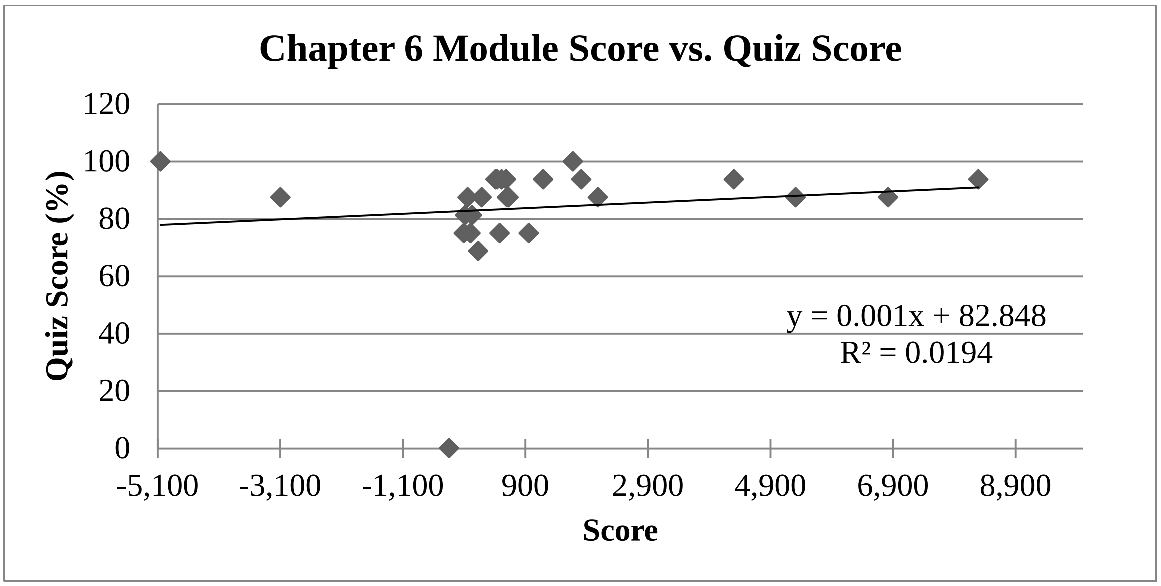

Figure 37. LearnSmart™-generated student score versus Chapter 6 quiz score ($p > 0.20$).

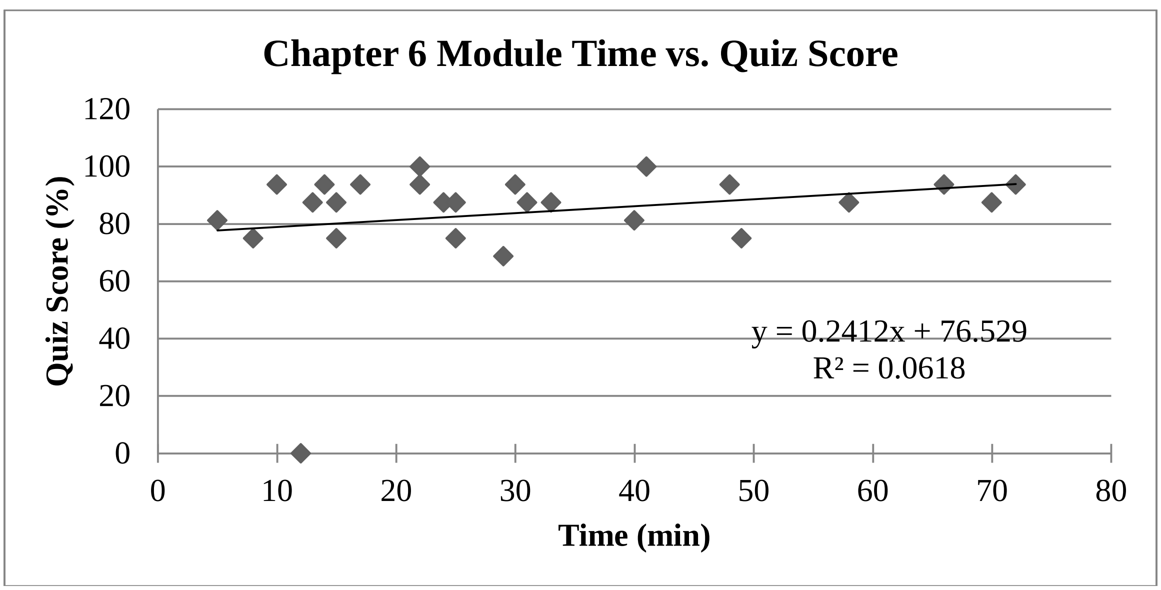

Figure 38. Time spent on LearnSmart™ cellular respiration module versus student Chapter 6 quiz score, excluding students who did not use LearnSmart™ for Chapter 6 ($p > 0.20$).

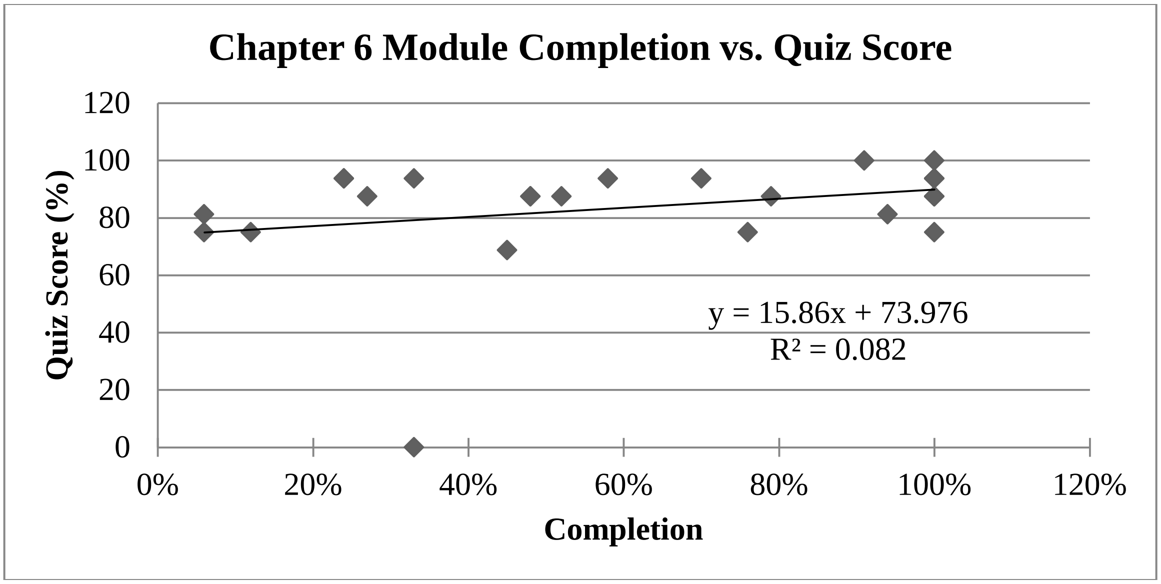

Figure 39. Percent completion of LearnSmart™ cellular respiration module versus student Chapter 6 quiz score, excluding students who did not use LearnSmart™ for Chapter 6 ($p > 0.20$).

Figures 40-43 explore linear relationships between the four categories of metacognitive data and Chapter 6 quiz score. The R^2 value was 0.0008 for the linear model of metacognitive: correct and aware versus quiz score, 0.0334 for the linear model of metacognitive: correct and unaware versus quiz score, 0.0006 for the linear model of metacognitive: incorrect and aware versus quiz score, and 0.0367 for the linear model of metacognitive: incorrect and unaware versus quiz score.

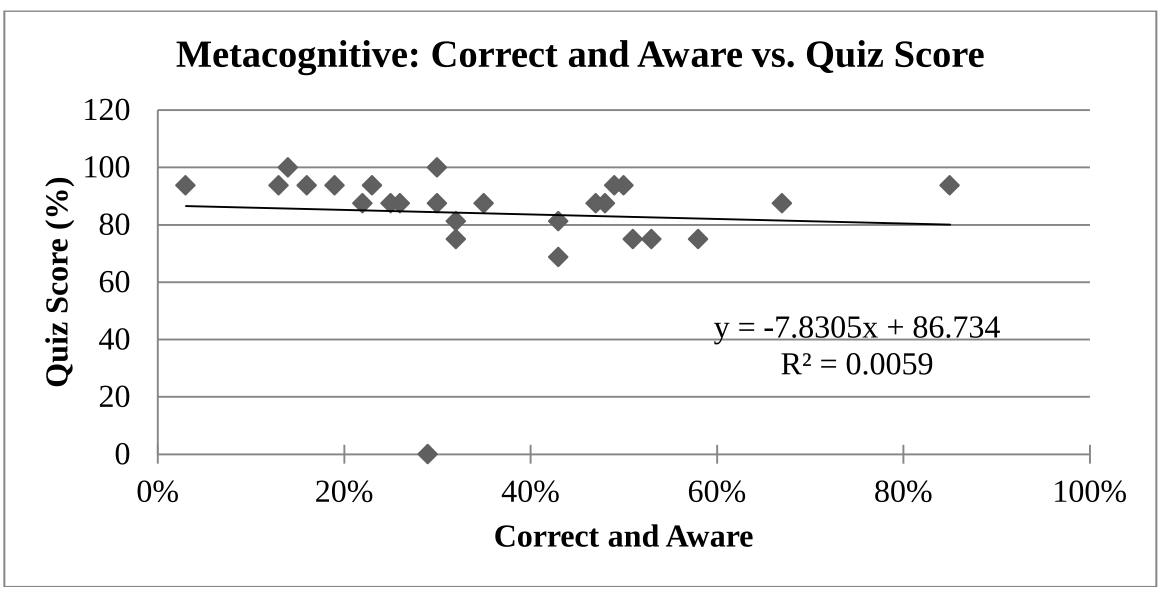

Figure 40. LearnSmart™ Metacognitive data (percent of questions answered correctly in cases where students selected that they were confident that they knew the correct answer) versus student Chapter 6 quiz score, excluding students who did not use LearnSmart™ for Chapter 6 ($p > 0.20$).

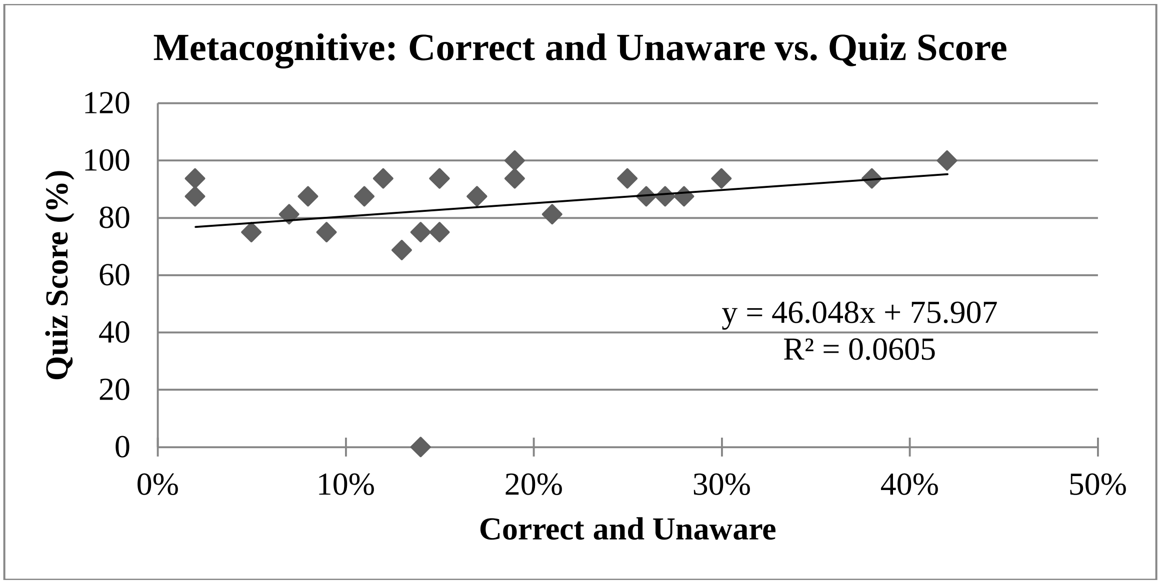

Figure 41. LearnSmart™ Metacognitive data (percent of questions answered correctly in cases where students selected that they were not confident that they knew the correct answer) versus student Chapter 6 quiz score, excluding students who did not use LearnSmart™ for Chapter 6 ($p < 0.20$).

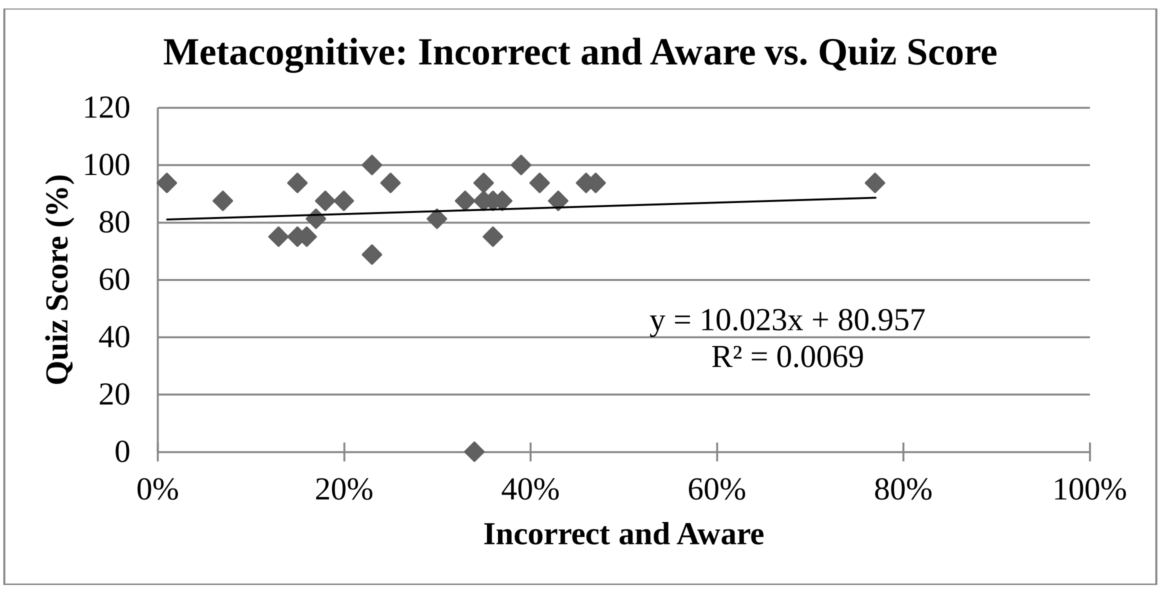

Figure 42. LearnSmart™ Metacognitive data (percent of questions answered incorrectly in cases where students selected that they were guessing-were confident that they did not know the correct answer) versus student Chapter 6 quiz score, excluding students who did not use LearnSmart™ for Chapter 6 ($p > 0.20$).

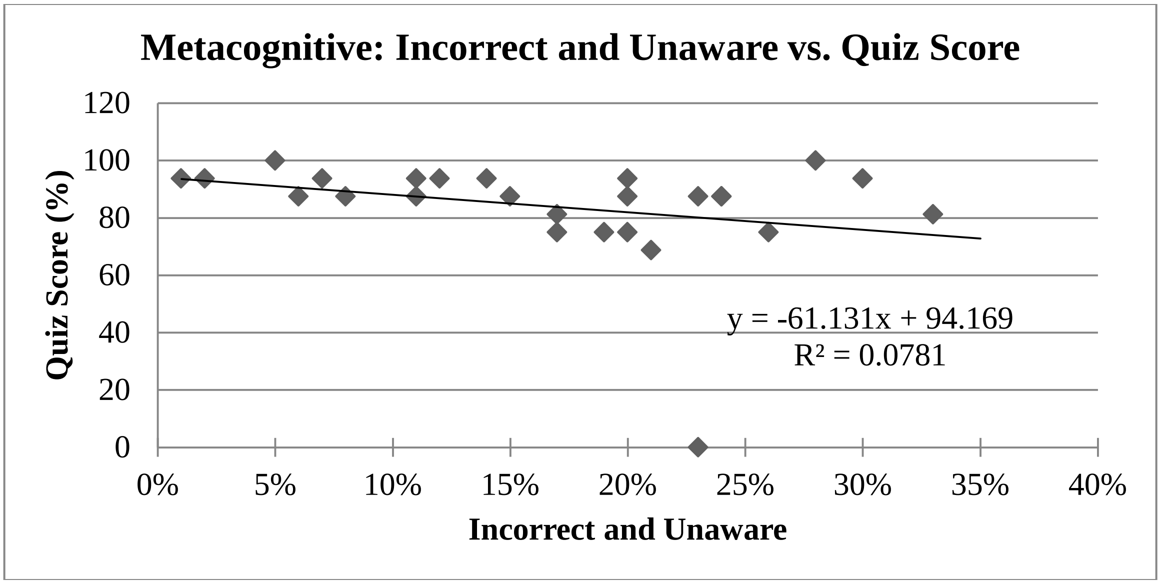

Figure 43. LearnSmart™ Metacognitive data (percent of questions answered incorrectly in cases where students thought that they knew the correct answer) versus student Chapter 6 quiz score, excluding students who did not use LearnSmart™ for Chapter 6 ($p > 0.20$).

Figure 44 examines the linear relationship between total time spent using LearnSmart™ and student Chapter 6 quiz score. Figure 45 examines the linear relationship between total percent completion of all LearnSmart™ exercises and student Chapter 6 quiz score. The R^2 value was 0.0384 for the linear model of total time spent on LearnSmart™ exercises versus Chapter 6 quiz score, and 0.0457 for the linear model of average total percent complete versus Chapter 6 quiz score.

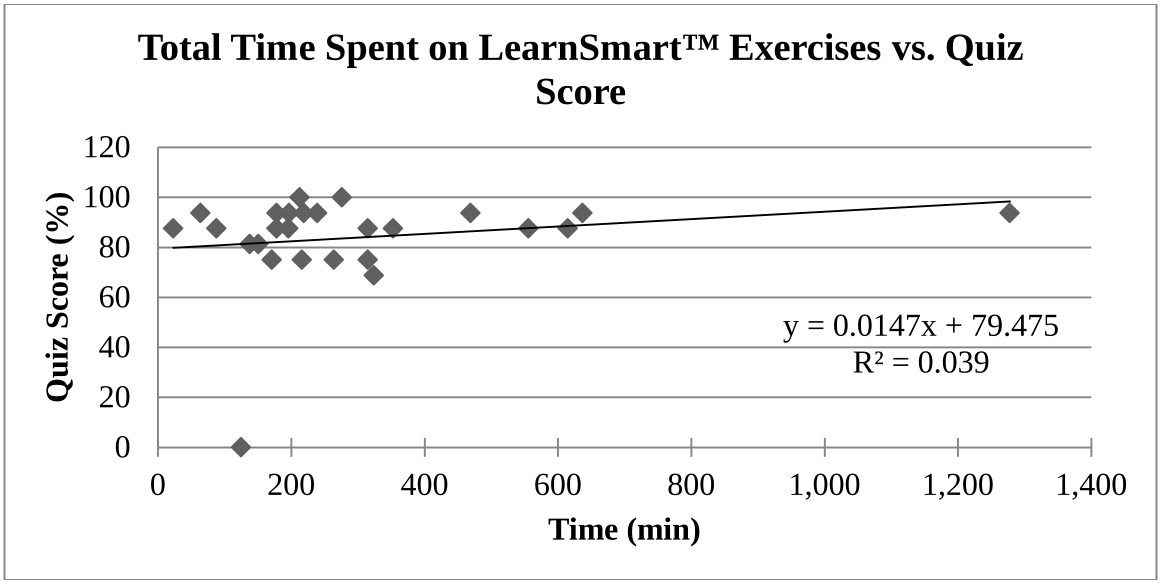

Figure 44. Total time spent on all LearnSmart™ exercises (including the cellular respiration module) versus student Chapter 6 quiz score, excluding students who did not use LearnSmart™ for Chapter 6 ($p > 0.20$).

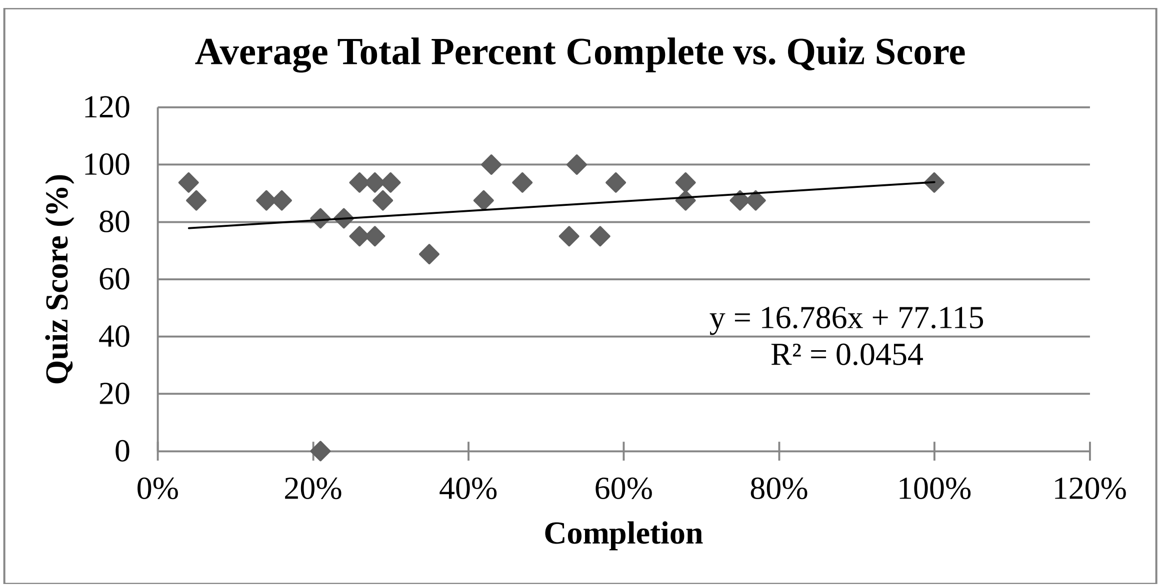

Figure 45. Average percent completion of all LearnSmart™ exercises (including the cellular respiration module) versus student Chapter 6 quiz score, excluding students who did not use LearnSmart™ for Chapter 6 ($p > 0.20$).

Data Set Five. The following figures are linear regression analyses of further revised data, removing outliers (the sample minimum and maximum) for total time spent on all LearnSmart™ exercises as well as Chapter 6 module time. As such, the first analysis was performed on the 60 records reflecting any LearnSmart™ use without the sample minimum and maximum. The second analysis was performed on the 28 records reflecting LearnSmart™ use for the Chapter 6 module without outliers.

a. (n = 58). Figure 46 explores the linear relationship between total time spent on all LearnSmart™ exercises and exam 2. Exam scores are out of 100.

The R^2 value was 0.0772 for the linear model of total time spent on all LearnSmart™ exercises versus exam score.

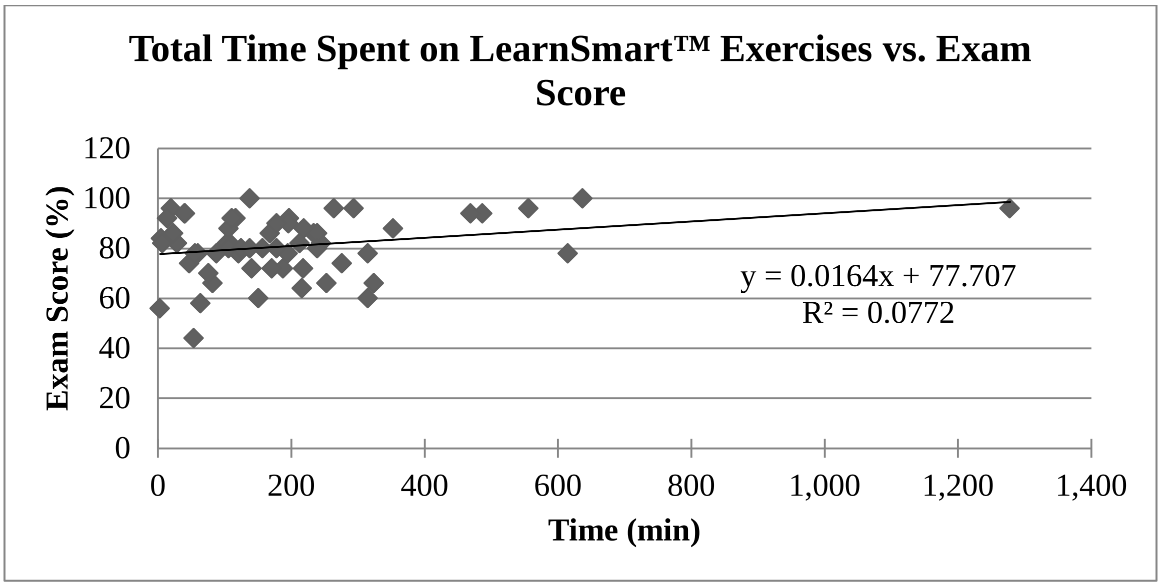

Figure 46. Total time spent on all LearnSmart™ exercises versus exam score with outliers removed ($p < 0.20$).

b. (n = 26). Figure 47 explores the linear relationship between time spent on the Chapter 6 module and Chapter 6 quiz score. Quiz scores are out of 60. The R^2 value was 0.0618 for the linear model of time spent on the Chapter 6 module versus Chapter 6 quiz score.

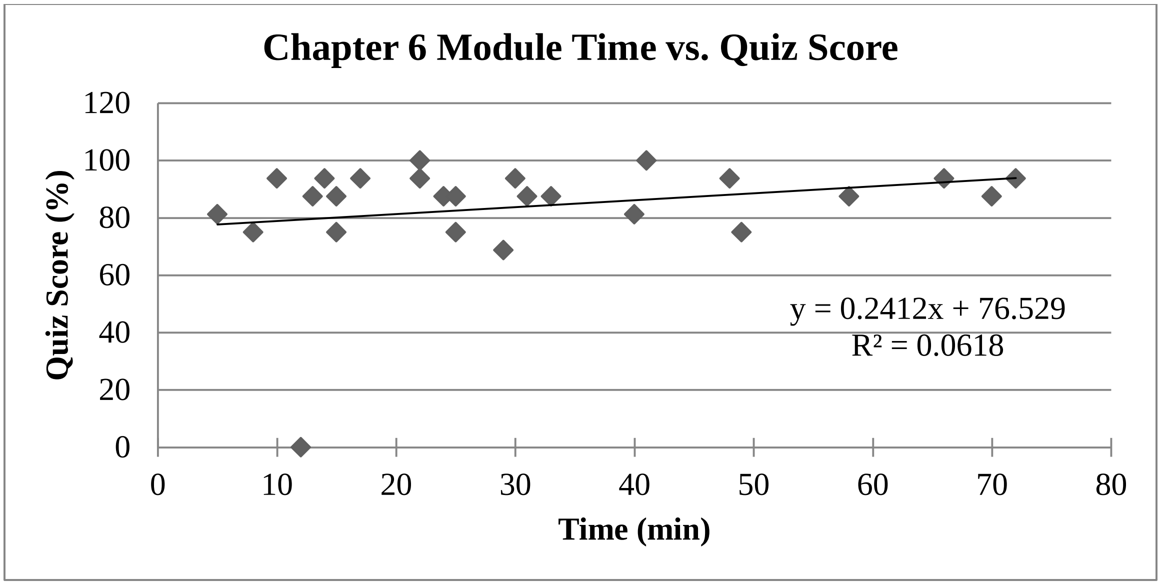

Figure 47. Time spent on Chapter 6 LearnSmart™ module versus Chapter 6 quiz score with outliers removed ($p > 0.20$).

Student LearnSmart™ Usage Survey

A complete summary of responses to all questions in this survey can be found in Appendix B. Based on a free-response question regarding what students particularly like about LearnSmart™ (Table B1), undergraduate biology students report liking:

- Visual appeal (4 of 93 responses)
- Variation in question types (9 of 93 responses)
- Use in practice (34 of 93 responses)
    - Quizzes
    - Flashcards
- Ease of accessibility (5 of 93 responses)
    - Including the option to work on exercises on their own schedule
    - The website can be loaded and navigated on an iPod, iPhone, or iPad.
- Immediate feedback (11 of 93 responses)
    - If a response is incorrect, an explanation is provided with reasoning as to why the incorrect response was wrong.

    - When a student answers several questions regarding the same learning outcome(s), the program redirects them to the text to review the content they are struggling with.
- Being held accountable for information they do not know (9 of 93 responses)
    - Questions that are answered incorrectly are repeated, but restated.
    - If student report that they are confident they know an answer, and get it wrong, a question is repeated or they are re-directed for remediation.
    - If students report they are just guessing the response, the question is repeated.

DISCUSSION

The goal of this study was to explore the potential influences of the features LearnSmart™ on student performance, with the goal of not only optimizing the learning experience for the student, but also providing meaningful assessment information for the instructor. . This research sought to explore potential relationships between assessment scores when aspects of LearnSmart™ were treated as predictors. These aspects included time spent using LearnSmart™, percent completion of LearnSmart™ exercises, metacognitive data, the LearnSmart™-generated student score, and traditional assessment data (quiz and exam scores). To examine the student's perspective on the adaptive learning technology, I collected voluntary student responses to a survey regarding the use of LearnSmart™ in their classroom (Appendix B).

From analyzing LearnSmart™ and assessment data from several angles, my goal was to establish specific aspects of LearnSmart™ that could be used as predictors for assessment performance. In addition, no matter the outcome of the data analysis, my goal was to utilize the data in this study to compile a list of best practices for use by instructors, so that they may successfully adaptive learning technologies in their classroom. As a result of the analyses performed in the course of this study, educators will be better able to better understand how LearnSmart™ is currently used as well as how it might be better used to maximize its effectiveness, both from an instructor and student perspective.

Comparing Average Assessment Scores

Though average Chapter 6 quiz and exam 2 scores were slightly increased with use of LearnSmart™ compared to non-use (Figures 4 and 5), use of the Chapter 6 module compared to non-use (Figures 6 and 7), and average percent completion of less than 50% or 50% or more of all LearnSmart™ exercises (Figures 8 and 9), none of these comparisons showed statistically significant differences.

Linear Relationships Between Time and Assessment Results

All Records (n=193). Time spent on the Chapter 6 module ranged from 0 to 93 minutes, while total time spent on all LearnSmart™ exercises ranged from 0 to 1,278 minutes. Exam 2 scores ranged from 40% to 100%, while Chapter 6 quiz scores ranged from 31.25% to 100%.

For exam scores, 0.008 % of the variation is explained by time spent on the Chapter 6 module (Figure 11) with a p value between 0.10 and 0.20, suggesting that this predictive relationship is in fact a trend. 1.71% of the variation in exam 2 score is explained by the total time spent on all LearnSmart™ exercises (Figure 17) with a p value less than 0.10, suggesting a strong trend in this predictive relationship.

For Chapter 6 quiz scores, 0.0068% of the variation is explained by the time spent on the Chapter 6 module (Figure 20) with a p value between 0.20 and 0.10, suggesting a possible trend in predicting quiz scores using Chapter 6 module time. 0.0034% of the variation in quiz score is explained by total time spent on all LearnSmart™ exercises (Figure 26).

Revised Data 1 (n=60). For student records with any data for LearnSmart™, total time spent on all LearnSmart™ exercises ranged from 3 to 1,278 minutes and Exam 2 scores ranged from 44% to 100%. For these exam scores, 3.07% of the variation is explained by time spent on the Chapter 6 module (Figure 29) with a p value less than 0.10, suggesting a strong trend in the relationship between Chapter 6 module time and exam score. 7.77% of the variation in exam 2 score is explained by total time spent on all LearnSmart™ exercises (Figure 35) with a p value less than 0.05, showing a statistically significant relationship between total time spent on LearnSmart™ exercises and exam score.

Revised Data 2 (n=28). For student records with data for the Chapter 6 module of LearnSmart™, time spent on the Chapter 6 module ranged from 4 to 93 minutes and Chapter 6 quiz scores ranged from 68.75% to 100%. For these quiz scores, 6.18% of the variation is explained by time spent on the Chapter 6 module (Figure 38); 3.9% of the variation is explained by total time spent on all LearnSmart™ exercises (Figure 44).

Further Revised Data 1(n=58). For records with any LearnSmart™ data that remained after the removal of the outliers, the sample minimum and maximum with regard to time, total time spent on all LearnSmart™ exercises ranged from 64 to 637 minutes and exam 2 scores ranged from 58% to 100%. 7.772% of the variation in these exam scores is explained by the total time spent on all LearnSmart™ exercises (Figure 46) with a p value between 0.10 and 0.20, suggesting a possible trend in this predictive relationship.

Further Revised Data 2 (n=26). For records with Chapter 6 module LearnSmart™ data that remained after the removal of the outliers, the sample minimum and maximum with regard to time, time spent on the Chapter 6 module ranged from 5 to 72 minutes and Chapter 6 quiz scores ranged from 68.75% to100%. 6.18% of the variation in quiz score is explained by time spent on the Chapter 6 module (Figure 47).

Overall, trends are seen in the relationship between Chapter 6 module time and exam score and Chapter 6 module time and quiz score (for all records and for overall LearnSmart™ users without outliers). Strong trends are seen in the relationship between total time spent on LearnSmart™ exercises and exam score (for all records) and for Chapter 6 module time and exam score (excluding students who did not use LearnSmart™ at all). A statistically significant relationship was observed when total time spent on LearnSmart™ exercises was used as a predictor of exam score (for students who used LearnSmart™ at all).

Linear Relationships Between Completion and Assessment Results

All Data (n=193). For all student records, percent completion of the Chapter 6 module ranged from 0% to 100% while average total percent completion also ranged from 0% to 100%. For exam scores, 1.7% of the variation is explained by completion of the Chapter 6 module (Figure 12), with a p value less than 0.10, suggesting a strong trend in this predictive relationship. 3.95% of the variation in exam score is explained by total average percent completion (Figure 18), with a p value less than 0.10, also suggesting a strong trend in this predictive relationship.

Revised Data 1(n=60). For the 60 records reflecting any use of LearnSmart™, percent completion of the Chapter 6 module ranged from 0% to 100%. Average percent completion of all LearnSmart™ exercises ranged from 1% to 100%.

For exam scores, 6.67% of the variation is explained by percent completion of the Chapter 6 module (Figure 30) with a p value less that 0.05, indicating a statistically significant predictive relationship. 9.78% of the variation in exam score is explained by average total percent completion of all LearnSmart™ exercises (Figure 36) with a p value less than 0.05, indicating a statistically significant predictive relationship.

Revised Data 2 (n=28). Of the 28 records reflecting use of LearnSmart™ for the Chapter 6 module, percent completion of the Chapter 6 module ranged from 6% to 100% while total average percent completion ranged from 1% to 35%.

For quiz scores, 8.2% of the variation is explained by percent completion of the Chapter 6 module (Figure 39) with a p value between 0.10 and 0.20, suggesting a possible trend in this predictive relationship. 4.54% of the variation in quiz score is explained by average total percent completion of all LearnSmart™ exercises (Figure 45).

Overall, percent completion of the Chapter 6 module shows a strong trend in its prediction of exam score, and a possible trend in its prediction of Chapter 6 quiz score when students who did not use LearnSmart™ for Chapter 6 were excluded. A statistically significant predictive relationship was observed for Chapter 6 module completion and average total completion as a predictor of exam score when students who did not use LearnSmart™ at all were excluded.

Relationship Between Metacognitive Data and Assessment Results

Complete Records (n=193). For exam scores, 0.30% of the variation is explained by answer choices categorized as correct and aware (Figure 13), 1.27% of the variation is explained by answer choices categorized as correct and unaware (Figure 14), 0% of the variation is explained by answer choices categorized as incorrect and aware (Figure 15), and 0.2% of the variation is explained by answer choices categorized as incorrect and unaware (Figure 16).

For quiz scores, 0.09% of the variation is explained by answer choices categorized as correct and aware (Figure 22), 0.07% of the variation is explained by answer choices categorized as correct and unaware (Figure 23), 0.07% of the variation is explained by answer choices categorized as incorrect and aware (Figure 24), and 0.05% of the variation is explained by answer choices categorized as incorrect and unaware (Figure 25). None of these analyses, for predicting quiz scores or exam scores, produced p values that indicated any trend or otherwise statistically significant relationship.

Revised Data 1 (n=60). For exam scores, 0.30% of the variation is explained by answer choices categorized as correct and aware (Figure 31), 1.27% of the variation is explained by answer choices categorized as correct and unaware (Figure 32), 0% of the variation is explained by answer choices categorized as incorrect and aware (Figure 33), and 0.20% of the variation is explained by answer choices categorized as incorrect and unaware (Figure 34). None of these analyses produced p values that indicated any trend or otherwise statistically significant relationship.

Revised Data 2 (n=28). For quiz scores, 8.17% of the variation is explained by answer choices categorized as correct and aware (Figure 36), 10.77% of the variation is explained by answer choices categorized as correct and unaware (Figure 37), 5.26% of the variation is explained by answer choices categorized as incorrect and aware (Figure 38), and 3.58% of the variation is explained by answer choices categorized as incorrect and unaware (Figure 39). None of these analyses produced p values that indicated any trend or otherwise statistically significant relationship.

Overall, the results of analyzing the metacognitive data do not show any particular category to be a very strong predictor of assessment performance for a class as a whole. This is logical, considering that metacognitive data is focused on an individual and not on a group.

Though the results may not tell an instructor anything about a class overall, they can be useful on an individual basis. To that end, it is important that instructors know enough about how to find and read these reports to use them for advising and other one-on-one meetings with students, and to inform students about these reports and how they can be used for self-assessment and reflection on learning.

Relationship Between Student Score and Assessment Results

The student scores in LearnSmart ™ are a function of the student's perception of their understanding of the material (the metacognitive data) and the correctness of their response. For example, a student who states that they know the answer but get the probe wrong, will lose more points than a student who states that they do not know the answer and miss the probe. LearnSmart ™-generated student scores ranged from -5053 to 8294.

All Records (n=193). For exam scores, 15.2% of the variation is explained by the student score (Figure 10) with a p value less that 0.05, indicating a statistically significant relationship. For quiz scores, 2.5% of the variation is explained by the student score (Figure 19).

Revised Data 1 (n=60). For students who used LearnSmart™ at all, 15.2 % of the variation in exam score is explained by student score, with a p value less than 0.05, indicating a statistically significant relationship.

Revised Data 2 (n=28). For students who used LearnSmart™ for the Chapter 6 module, 1.94% of the variation in quiz scores is explained by the student score (Figure 37).

Overall, student score is a useful predictor of exam scores but not quiz scores. Though it could prove useful for students who enjoy the "gaming" aspects of LearnSmart™ and benefit from a competitively challenging learning environment, this feature can be turned off for students who do not wish to feel they are competing with their classmates.

Development of Best Practices

In part because the data from this study show that the time, completion, metacognitive, and student score reports are not great indicators of class-wide performance, but more so because of the demonstrated need for experience-based information on the implementation and use of adaptive learning platforms like LearnSmart™, I aimed to develop and include a set of best practices in the conclusions of this study. The development process included examination of the literature and identification of areas in which it was lacking, research into case studies published on LearnSmart™ use via the Connect Community website (www.TheConnectCommunity.com), a part of McGraw-Hill Higher Education, and the opinions and recommendations of the non-majors students in the course used in this study, as expressed through the voluntary student LearnSmart™ use survey.

LearnSmart™ is a student-centered program that, based on several case studies, has been shown to increase student retention , help maintain student engagement, and increase student performance, while making instructors more efficient by providing them with "valuable data" to help students master course material (Wray, 2009). Professors involved in these case studies recommend LearnSmart™ from experience teaching courses on a range of subject matter (including accounting, algebra, biology, and anatomy and physiology), using several course formats (including traditional, hybrid, and online designs). The subjects of the studies included courses with enrollment ranging from 30-152, in colleges and universities across the United States. LearnSmart™ was employed for various reasons by these instructors. Some hoped to standardize course content across multiple sections being taught by various instructors, others to free up more of their own time, and some to begin or better offer course content online (Wray, 2009; Streibich, 2009; Hoover, 2009; Donahue, 2010).

Aside from cost, some of the complaints or suggestions for improvement of LearnSmart™ gathered from the student survey (Table B2) indicate that students are not aware of some of the platform's features and/or how to use them, including its practice quizzes and the option to disable the student score from being publically viewed. This reiterates the need for an improved understanding of how to use LearnSmart™, which might indicate the need for increased or adjusted quality of, instructor training and/or a more in-depth student orientation to this technology.

The student responses to this survey also overwhelmingly indicate that students view LearnSmart™ as helpful. When asked if they thought that using LearnSmart exercises had improved their performance in the study class, 75% of students responded" yes" (Table B3). And, despite the fact that LearnSmart™ was not required for the course, of the 92 students who responded to the question "Do you use LearnSmart exercises to prepare for exams in this class?", 74 reported that they did. Out of these, 36 students reported using LearnSmart™ to study for about one half of class exams, 15 for about 80% of class exams, and 23 for every exam (Table B6). The lack of mention of the various LearnSmart™ reports seems to indicate that students are not using the reports to their advantage, for self-assessment and reflection on learning. If they were introduced to this information, it might help students with practice and studying, which they already report liking (Table B1).

The majority of the data analysis herein demonstrates that LearnSmart™ reports do not serve as good indicators at a classroom level. However, we did not analyze, or even mention, all of the reports offered by this platform. From an instructor perspective, perhaps the most useful aspects for classroom assessment are the Most Challenging Learning Objective, the Module Details, and the Missed Questions reports (Figures 48-50).

- module: Chapter 6. How Cells Release Energy

Root objective	Name	Page
How Cells Release Energy	Know where the steps of aerobic respiration occur in different organisms	107
How Cells Release Energy	Know how pyruvate is oxidized	109
How Cells Release Energy	Know the summary of products leading up to electron transport	109
How Cells Release Energy	Define chemiosmotic phosphorylation	109
How Cells Release Energy	Define mitochondrial intermembrane compartment	107

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Figure 48. Chapter 6 LearnSmart™ Module "Most Challenging Learning Objectives" Report. This includes the root objective, the text of the learning outcome as seen in the text book, and the page number corresponding to the area in the text in which this objective is addressed.

Assignment dates: 04/05/12 to 04/19/12
Number of assigned items: 17

Chapter section	Average time spent (hh:mm:ss)	Average questions per student correct / total	Correctness 0% 100%	
Cellular Respiration	N/A	26 / 27		94%
Nad and Fad	N/A	N/A	N/A	N/A
Cellular Respiration	N/A	26 / 27		94%
Outside the Mitochondria: Glycolysis	N/A	4 / 5		92%
Fermintation	N/A	3 / 4		93%
Advantages and Disadvantages of Fermentation	N/A	N/A	N/A	N/A
Inside the Mitochondria	N/A	8 / 9		93%
Metabolic Pool	N/A	2 / 2		94%

Figure 49. Sample Module Details Report for the Cellular Respiration Module.

Frequency	Question
13	Which of the following are produced during cellular respiration? (Try probe)
12	Define cellular respiration (Try probe)
12	Fatty acids are converted into _______ CoA which then enter the Krebs cycle. (Try probe)
12	Which process produces lactate? (Try probe)
11	Which of the following are products of cellular respiration? (Try probe)
11	All of the following are components of glycolysis EXCEPT: (Try probe)
10	The net ATP production for glycolysis is the same as that for the Krebs cycle, each producing ______ molecules of ATP. (Try probe)
10	The electron transport chain produces 32-36 molecules of ______. (Try probe)
10	During glycolysis, ATP is produced via: (Try probe)
10	Which of the following is an input to the citric acid cycle? (Try probe)

Figure 50. Sample Missed Questions Report for the Cellular Respiration Module. This includes the missed question (text) and the frequency with which it was missed.

These reports could be used, for example, if an instructor deploys LearnSmart™ prior to a class/lecture meeting. The instructor can run these reports, allowing for on-the-spot tailoring of the day's lecture to meet the demonstrated needs of the students. When students work with LearnSmart™ before scheduled lectures, these reports take the guess-work out of planning for instruction, and can be repeated for every section during every semester with just the click of a button. Using these reports is also a great alternative to in-class diagnostic exams.

It should be noted that, to date, there have not been any attempts to assess whether the use of these reports by the instructor has any meaningful impact on student performance, retention, or understanding. Future studies should be conducted to assess these relationships and establish best-practice documentation for instructors who use adaptive learning technologies.

Conclusions

When examining class LearnSmart™ data, the best predictors of student assessment scores are student score (for exam scores), module completion (for exam scores), total time (for exam scores) and total average percent completion (for exam scores). None of the predictors I looked at were statistically significant predictors for quiz scores. It is logical that percent completion and time would be strong indicators of exam performance, since more interaction with material would seem to strengthen student understanding. Also, with built-in feedback and other adaptive qualities, the time invested in LearnSmart™ could prove to accomplish more than standard studying practices.

It would be beneficial to examine a class that was required to use LearnSmart™ in order to make significant statements about the statistical trends observed for other predictors, though these were all related to time and completion. Metacognitive data did not provide a strong predictor for any data set. This data is most likely best-suited for student self-reflection and instructor/student discussions of student progress and study skills. It is also important to note that the student survey data and past case studies have indicated student and instructor satisfaction with this adaptive learning platform. Compiled based upon these successful experiences, my own teaching and learning experiences and research on adaptive learning in education, and the instructional experiences using LearnSmart™ of my faculty advisor Dr. Michael Windelspecht, the following are several pointers that aim to assist in the successful implementation, or improved continued use, of adaptive learning technology.

General Best Practices

1. In creating a course and writing a course description, outline important differences between your course and traditional course, and include helpful tips regarding required learner qualities. Include information like technology requirements, independent vs. group work, and time spent working outside of class.

2. Especially for wholly online courses, introduce yourself and how the class will operate early on. Use video tutorials where appropriate. This can help to create a personal connection to what can be a highly mechanized learning experience.
3. Understand the ALT you decide to use. Do not expect your students to anything with the ALT that you cannot do yourself.
4. Run demonstrations in class. In addition to tutorials, running a few simple introductory demos, or "how to" sessions, can save time in the long run. Think of things students would want to do with the technology, including completing an exercise, checking a grade, or using the built-in features (like links from the exercises to an online textbook, etc).
5. In creating exercises, preview everything in "student mode" to avoid problems down the road with grading, etc.
6. In creating exercises, design short assignments. As a general rule, aim for assignments that can be completed in 20-30 minutes.
7. Assign material early. To give students plenty of options for when and where to complete an assignment, and in some cases, the opportunity to repeat the assignment to earn a better score, assign it 4 to 5 days before it is due.
8. Allow for a learning curve with regard to technology. Scaffold technology just like you would scaffold learning. In the beginning, administer simple exercises, without time limits and with multiple attempts, to leave room for error. Later on, limit time and attempts to encourage student proficiency and to increase the challenge of an exercise.
9. Adapt materials. Just like "borrowing" a lesson, a hand out, or a test made by someone else, tailor the adaptive learning assets to suit your needs, and the needs of your students. This will make questions and exercises endlessly flexible and reusable.
10. Use the built-in features of the ALT to your advantage. For instance, when meeting with a student one-on-one, pull up the reports the ALT generates based upon the student's use and discuss them with the student.

Specific Suggestions for LearnSmart™

1. When a student comes for one-on-one assistance, or you bring a student in for intervention, advising, etc:
    a. ***Review the metacognitive data.*** This information can be used to investigate several things:
        i. If students are better guessers than they think, which may mean that their core content knowledge is stronger than they think, there will be a significant percentage of responses in the "correct and unaware" category.
        ii. Conversely, a large percentage of responses in the "incorrect and unaware" category would mean that students think they know more than they do, and are in need of review.
        iii. Large percentages of responses in the "incorrect and aware" and "correct and aware" categories would confirm that students are fully conscious of material that they have mastered and need to review. However, seeing this in the reports can serve as a useful reminder, particularly if the students are reviewing for an assessment (especially something cumulative).
    b. ***Review the time data.*** Showing a student how much time they are actually spending on the material can bring a realistic awareness of the investment s/he has made in the material.
        i. If students have invested a great amount of time and is still falling short on assessments, it may be necessary to look at time spent on materials in conjunction with other reports (i.e. percent completion/ average percent completion).
        ii. If students have invested little time in the materials (or less than s/he would otherwise admit), looking over this report with the students could help open a

discussion about how much time is *recommended* by the instructor (based on hours of credit earned for the course, etc.).

   c. ***Review the percent completion data.*** Students may be spending too much (or too little) time on exercises and not be aware. If so, students might not realize:

      i. That they are investing too much time t*o complete o*nly a small amount of the material (and that they should make repeat attempts since LearnSmart™ exercises do not report a percent correct score).

      ii. That they are investing too little time and thus completing only a small percentage of the total material available. In this case, they should be encouraged to spend more time in order to increase exposure to the material, since more exposure generally leads to better assessment scores.

2. When examining classroom level data,

   a. ***Review the most challenging learning outcomes.*** This report details the learning outcomes and the pages on which the associated material can be found. Use this information to tailor daily and lectures and/or assign extra practice in areas where the class in struggling.

   b. ***Review the missed questions.*** This report lists the most-missed questions and the frequency with which they were missed. Use this information to tailor lectures and/or assign extra practice in areas where the class is struggling.

   c. ***Review the module details report.*** This report includes the average time spent and associated percent correctness by module topic. Use this information to tailor lectures and/or assign extra practice in areas where the class is struggling.

Future Directions

Some obvious problems come with this kind of study. The first is that not all students are well-suited to learn in an online platform. The second is that not all content is suited to be delivered in this manner. Having been a student and an instructor in the sciences, I hope to continue my research in science education in order to hone in on the aspects of introductory biology that can be delivered most effectively using digital media, as well as the type of student that is best-suited to learn via traditional lecture, via hybrid courses, and via exclusively online courses.

Eventually, I would like to create generalized learner profiles that could be used to lead a student to the format of instruction that would suit them best. This is tricky, since no matter the results of a study, there will always be exceptions. In studying student outcomes many variables are intertwined, to include student attendance, subject background, and personal goals and motivations in approaching a course. Some students will complete all assigned practice (homework, reading, projects, etc.), attend every study session, and use any supplemental material provided. Other students are content to put in only the minimal amount of work required to pass a course. Another subset altogether may be entirely disinterested in grades and their coursework due to countless reasons having nothing to do with the quality or nature of instruction. However, it is my goal to continue to add to the best practices included with this study to aid instructors as they integrate digital media and adaptive learning into their classrooms, taking into account that even the best of plans will not work for every student every time. I hope to include the most successful methods for setting up an online or hybrid course, making adjustments throughout the course, and where to find support in the form of materials, tutorials and technical support in the event that an instructor encounters problems.

Taken altogether, my research aims to make changes that will not only raise student grades, but will positively influence retention rates in the sciences as a whole. Due in large part to its sheer quantity, along with current methods for its delivery and assessment, undergraduate biology course content is a major factor in influencing whether a student continues with plans to pursue long-term goals to study within the sciences (i.e. pre-med or other pre-professional tracks) (Spall *et al.*, 2003).

By helping students and teachers to comfortably transition into new methods of teaching and learning, educators can finally start to address many of the problems that science education currently faces, especially bearing in mind that in order for adaptive learning to really work, a few things must happen: First, instructors (or colleges and universities), must invest time in adopting technology that suits the needs of the course(s) it hopes to hybridize or offer solely online. This will require some research and experience testing the technology before jumping in head first. Though exercises may be pre-populated into existing technologies, instructors must also be willing to share and develop new learning tools, such that a large reusable pool of exercises can be amassed. Materials must be available to address the subject matter at a variety of levels, from simple exercises in remembering and understanding to complex exercises that require analysis and application.

Next, instructors must not rely on the adaptive nature of technology to produce results. The instructor must retain the responsibility of student learning by actually using the data generated by the technology to make applicable changes to the course.

Finally, students must spend time, and be given support in, learning to navigate the learning environment. Adaptive learning presents a range of promising formats for changing the way we teach and learn. If we exploit these tools to their fullest potential, students and instructors can reap the benefits and the education system can continue to make important changes in our science classrooms.

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APPENDIX A

IRB EXEMPTION

From: Robin Tyndall, Institutional Review Board
Date: 2/28/2012
RE: Notice of IRB Exemption
Study #: 12-0194

Study Title: Effects of Adaptive Learning Technology on Undergraduate Biology Education
Exemption Category: (1) Normal Educational Practices and Settings

This submission has been reviewed by the IRB Office and was determined to be exempt from further review according to the regulatory category cited above under 45 CFR 46.101(b). Should you change any aspect of the proposal, you must contact the IRB before implementing changes to make sure the exempt status continues to apply. Otherwise, you do not need to request an annual review of IRB approval. Please notify the IRB Office when you have completed this study.

Best wishes with your research!

APPENDIX B

ASULearn LearnSmart Student Survey

The purpose of this survey is to investigate the effects of technology on education. Your participation in completing this survey is voluntary and you may decide to stop at any time for any reason with no penalty, or you may choose not to answer any of the survey questions. All responses will be kept confidential. You will be asked to complete 6 questions regarding LearnSmart; this process should not take more than 15 minutes. Benefits of this research include improvements in the way we use technology in the science classroom. This could improve student performance.

If you have any questions or concerns about the nature of this research or the survey please contact:

Dr. Michael Windelspecht, Associate Professor of Biology
Appalachian State University
572 Rivers Street
Boone, NC 28608
828- 262-3025
windlspchtm@appstate.edu
or email irb@appstate.edu.

Survey Questions:

By continuing to the survey, I acknowledge that I have read the above information, and provide my consent to participate under the terms above.

1. What do you particularly like about LearnSmart?
    Free response

2. What would you change/improve about LearnSmart?
    Free response

3. Do you think using LearnSmart activities has improved your performance in this class?
    Multiple Choice:
        Yes
        No

4. Approximately how much time do you spend per week using LearnSmart?
    Multiple Choice:
        Less than an hour
        1-2 hours
        3-5 hours
        More than 5 hours

5. How is LearnSmart being used in your class?
Multiple Choice:
It is a non-graded supplement to lecture
It is a required graded part of class work
It is extra credit

6. Do you use LearnSmart to prepare for exams in this class?
Multiple Choice:
Yes always- 100% of the time
Yes often- about 80% of the time,
Yes sometimes- about 50% of the time
No never

The following tables and figures summarize the student response data for the optional student use survey. Not all students answered all questions. Student number does not correspond in any way to individual students or to the student research identification number found in the materials and methods section of this study. Only minor formatting changes were made to student responses, including spelling, capitalization, and minor grammar corrections.

Table B1. Question 1 Responses (What do you particularly like about LearnSmart?).

Student #	Question 1 Response
1	I don't have to use flashcards that i have to make, and can just use the ones on the internet, which generally are better than the ones i would make. Quick access to good material.
2	It has you say if you really know the answer or not so that way if you are just guessing but get it right, it puts it back in the pile until you actually know the answer and you aren't just guessing.
3	I like the flashcards on LearnSmart. They really help and if you get them wrong they are put back into the pile until you get them right.
4	I like knowing my grade as soon as the test is complete
5	I like that it shows the material in multiple ways to help you better understand the material.
6	I liked that it was a good way of quizzing what you have learned. Also that it had different ways of answering (short answer, multiple choice...).
7	I like how it's an interactive way for students to learn that is outside of the classroom.
8	That it remembers which flashcards I need to work on more.
9	I don't really know anything about LearnSmart.
10	That the questions aren't ones that are obvious. It is challenging and makes you do your research so you actually learn. It makes me learn in a different way. I'm competitive and it helps me stay engaged while learning.
11	I really just liked the use of LearnSmart. I struggle in biology and LearnSmart was a great way of helping me not only memorize the material, but help me understand it. I

	find LearnSmart a great alternative then visiting professor's office hours and wasting their time.
12	It helps me when studying. I am a visual learner so looking at the information allows me to remember it better. It is a very fast program.
13	I like LearnSmart because it allows me to take practice quizzes for the exam and I feel like I am learning more by looking at LearnSmart. It gives me a lot of practice.
14	I find that reviewing the practice questions prepares me for our exam. It quickly shows me what i need to improve or review before the test.
15	It is a very helpful study buddy. I particularly like the fill in the blank questions; those seem to pop up on the test the most.
16	LearnSmart had a unique flashcard system that helped me study for my exam.
17	To be honest, i do not know what LearnSmart is.
18	I like how it narrows down which definitions you don't know.
19	I like how it will ask a question you get wrong in a different way than it was first stated.
20	I like learn smart because it give you the pages you should go to that will help you better understand what your messing up on. As well it makes studying a lot more interactive and fun.
21	It helps me study for test
22	Easy to navigate, easy to find assignments. Automatic grades after quizzes and tests.
23	It helps organize the material I need to study.
24	I like it because it gives me quick and easy access to the information from class
25	The close interaction and allowing you to learn the information before moving on unlike lecture class.
26	It gives questions with simple wording and it suggests things to look over which helps me realize what items I need to spend more time focusing on.
27	I wouldn't know. I have never used learn smart before.
28	I think it’s a great and effective way to train students on certain topics on their own time. Sometimes busy schedules interfere with one's learning, so being able to learn at your own pace and time is very important.
29	I really enjoy the way that the quizzes refer us to a part of the textbook if we are having difficulty answering certain kinds of questions.
30	It is a very helpful extra tool. For me at least, textbooks aren't always enough, for example, I need more elaborate details explained in order to fully grasp the concepts, which is the whole purpose of this course: to understand biological concepts.
31	I like the flash card practice questions. i think they are a very useful study tool
32	I have not used it a lot, but the times I have used it, it has been very effective in helping me understand the material better
33	What I like about LearnSmart is the way it tells you the correct answer if you miss the question and it gives a reasonable explanation on why it is the correct answer.
34	I like how if you get a question wrong, it puts the note card back into the stack and makes you re due the question until you get it right.
35	The study resources
36	I like the flash cards because it saves me the hassle of making my own.
37	I actually have never used it.
38	I have not been using LearnSmart
39	I like how it asks a variety of questions and has some short answer and multiple choice. I like the questions with the diagrams because it provides a picture for visual learners. Some of the questions seem a little difficult which helps prepare for the upcoming tests.

40	I have never used LearnSmart.
41	I am a very visual person, so I like having something else that I can look at to study with. I think it is very helpful to have another source in preparation for studying.
42	I have not used it very often it didn't help much; on the occasions I did use it.
43	It helps me learn better. And understand the topics more then I would if I learned them on my own.
44	I love how it allows me to answer questions and how it provides me answers to the questions I miss. I am then able to visit the question I missed and able to attempt the question again. I used it religiously on my first test and got a 94. I also like how you are able to compete with classmates.
45	It helps me to better understand that information that we go over during the lectures.
46	The fact that I can practice and apply what I have been learning. I like the quizzing system as I believe that to be the most effective method of studying for me.
47	Ability to work practice problems.
48	I like that Learn Smart enables students to connect with their material online, outside of the resources gleaned from textbooks and the power points. I also like that students are able to use their cell phones and Learn Smart!
49	LearnSmart offered an array of in-depth flashcards that tested multiple facets of material in a complex and diversified manner, all the while, offering a simplistic system upon which reliable and dependable to cover the main course of work of each chapter.
50	I like being able to learn interactively with LearnSmart
51	I like how it takes the questions you do not answer right and brings them back up for a retry. This makes sure you know the correct answer.
52	How it gives the book perspective so I get lectures and book help
53	I really like how when you get a question wrong on the flash cards it will tell you what you are struggling with and where you can find it in the book.
54	It is short answer. You don't have to read a paragraph or a long story. It's just short and straight to the point.
55	I like its flashcard style learning and how it really helps me learn the material for each chapter.
56	It gives a preview of the type of questions that could be on a quiz and recaps all the information in the chapter.
57	The fact that the information is easily available and covers a variety of topics.
58	I have never used LearnSmart. Furthermore I have never heard of LearnSmart until this questionnaire. I have earned a solid B average from just attending the lectures and studying the book. If you have to pay extra for LearnSmart I would not invest the money, because I have a book and a professor to teach me the material.
59	I like how easy it is to use and understand.
60	I have not previously used the LearnSmart application. None of my current teachers require it, or have recommended it.
61	It's a great way to help you memorize information.
62	I like that when you take the quizzes, they give you the questions that you missed again in order to help make sure that you learn the material.
63	I like how questions that you missed are reentered into the stack so that you have to learn the material. I also like how there are different types of questions so that you can stay focused on the material for a longer period of time.
64	It lets me go into more depth on certain subjects that I don't particularly understand.
65	Helps me get the basic on studying.... I do better with flash cards
66	I believe that it is a very useful program and effectively teaches students terminology.

	I like the way that they ask you how confident you feel in your answer, and the way that it brings back the questions that were incorrect later to help you remember them.
67	I think that it is easy to use, and it presents the material in a different and refreshing way.
68	I like that it repeats the questions you miss, or seem unsure about
69	The LearnSmart program helps me study for my quizzes and test
70	it is my way of studying and helps me understand key words
71	It makes it easier to know how, and what to study.
72	I like that it has a variety of question that pertain to the subject matter. It allows me to see what I do and do not know.
73	I think that it is a great, organized idea to study and figure out different assignments.
74	It is easily accessible.
75	It gives opportunity to make flash cards and quiz you on each chapter giving a review of the chapter.
76	It can be programmed on an iPod/iPad
77	The questions seem to be very useful on the test. The questions ask more than one question and you have to know some background information to answer the questions.
78	i like the flash cards section they really simple everything down for you and give better chances for understanding everything
79	I like that LearnSmart is an helpful online learning tool and that its customized to adapt to the students weaknesses and strengths
80	The program covers a variety of material that is certain to be on the tests and quizzes.
81	I believe it definitely gives us a second and better visual of what we need to concentrate on.
82	The thing I like most about LearnSmart is that it grades you based on how you answer questions.
83	I have not used LearnSmart a lot, but the times that I did, I really loved the note card practice. I used them to study for our quizzes. I liked that you first choose how well you know the information, so if you don't really know the information, but take a lucky guess, the program still makes you look over the information again.
84	One of the things that I really like about Learn Smart is that it asks questions that you make you deepen your understanding of the chapter or topic. I think that allows you to really grasp what’s going on and understand it completely. I also like that it makes you think or search for the answer instead of just guessing on a multiple choice question.
85	I like how when you miss a certain amount of questions, it tells you what pages in the book you should read over again. It also re asks you the questions that you miss so that you can correct yourself. Also giving what percentage you are rated in the class gives you the competition to compare yourself to your other classmates.
86	I like how if you get a question wrong it brings it back up until you get it right and it shows you the right answer. I also like how it shows you where in the book to find the answer it is telling you is right.
87	I like the fact that it keeps giving you the same types of questions in different ways if you miss them.
88	When you answer a question wrong, the question shows up again to make sure you understand the answer.
89	Learn Smart helps you understand material that you have trouble understanding. It’s another way to study and you can do it with classmates to help as well. if you don’t like reading or your note taking is not up to par, learn smart is definitely a help
90	The use of flashcard like studying and the way it replaces questions I've answered

	wrong back into the pile.
91	I like that LearnSmart has multiple ways of asking questions about one topic. It really helps me to understand the concepts of the chapters.
92	I know nothing about LearnSmart.
93	How easy it is to use.

Table B2. Question 2 Responses (What would you change/improve about LearnSmart?).

Student #	Question 2 Response
1	More information that i can just read, instead of only flashcards. and at the bottom of the flashcard if you get it wrong, it restates it the correct way, but doesn't give ANY more information than the correct statement
2	Sometimes they try and "trick" you and ask you different questions about the same concepts even when you haven't mastered the first concept. So maybe they could stay on that one question until you get it right, and then rephrase it other ways to prove that we actually know the answer.
3	I don't like that once you have answered the flashcard correctly it goes away. I would like to be able to keep practicing even after I have gotten all the flashcards right.
4	I would like if it showed us what the correct answer was when we got them wrong so we would know to study for the tests
5	I really like how LearnSmart is right now; it displays the information clearly and easy to understand.
6	The questions seem to be a lot harder than the questions on the test because the way they are worded!
7	I would make the study guides more in-depth
8	That it would be a free site
9	The spread of information about LearnSmart. I've never heard of it before.
10	If the answer isn't spelt right or if the answer is more than 1/2 way correct to count it right. You may be one letter off in the spelling and it still counts it wrong even when you clearly know the concept.
11	I find LearnSmart was an effective study tool. All I would change is just making its presence more known and inform students of the benefits from utilizing this study tool.
12	More questions on material. More flashcards
13	Throughout the semester, I have not had any problems with LearnSmart. It has done nothing, but helped me. Therefore, I would not change it.
14	I would like to still answer questions even after I get some questions wrong. Usually it kicks me off after repeatedly missing questions and it would be more helpful for me if it didn't do that.
15	I don't really like the questions that have multiple answers only because I never get them all right.
16	I would make it more interactive - a more fun way of quizzing.
17	nothing
18	I want more interactive things so I can see what is going on. I never found any on there, I know there are pictures in the book but I'd like to see it move around and talk to me.
19	I would make it so the Professor could check what topics were actually taught in class. I will come across questions in the chapter that I have no clue about because our professor decided to not cover it on our test. So if the teacher could customize what subjects were covered in the chapter questions, it would be a better system.

20	If i could change Learn Smart I would make it a little bit more in depth and make it so students could do unlimited amounts of time on it.
21	I would allow you to use the questions even after you got them right..instead of taking them away
22	nothing
23	the cost
24	I think that it could possibly be better organized
25	Show more pictures and give examples that a younger person would understand.
26	The fact that it allows you to see the scores of other people on a particular section.
27	LearnSmart seems very expensive since packages are several hundred dollars. Personally I don't know the true cost of a real classroom experience. I do understand everyone needs to make money so I can't find that many improvements that need to be made.
28	I wish there was a way we could create our own questions from our lecture notes to be asked to us on LearnSmart randomly with the other questions since the exam material differs from the questions asked in the program.
29	Because it is so helpful I wish that it could be made free to students somehow.
30	have practice quizzes and tests for each chapter
31	There is nothing, at this time, that I would change about LearnSmart
32	What I would change about LearnSmart is trying to add a video for each chapter than covers the main vocabulary terms and key points or main ideas of each concept.
33	I do not like the question about how “confident” you feel about a certain question first because sometimes you may click you “ definitely know it” option then get it completely wrong, which makes it a little unnecessary.
34	make it more user friendly
35	Nothing. It uses a lot of the material we need for our class particularly.
36	I don't really have any suggestions.
37	Since I have not used LearnSmart I don’t know what to change
38	I would make some of the questions a little easier.
39	I'm not sure.
40	I honestly wouldn't change a thing. I think it works perfectly the way it is.
41	Nothing
42	Make it easier to use.
43	I can't think of anything to change. I really enjoy the program and feel as though it really helps me.
44	It works fine for me.
45	I wish the professor could customize it. I have found that roughly 40-50% of the questions do not apply to what I need to know for the class. So a lot of the questions I do not need to know.
46	Wish it wasn't so expensive... Glad it's only optional.
47	Nothing! It is easy to use and enroll in.
48	I would make it so that you could hit the “enter” button and it would accept the answer rather than having to click submit each time. Also, I would review the questions which are put forth as 'reworded questions that are asking the same thing' because they can be quite confusing, not because of the difficulty of the material but because the grammar and English used are just plain awkward.
49	Nothing.
50	Honestly, I would make it free. Also, I would take away the “Do you know it” part.
51	Make it more interactive

52	I would make is so that instead of having to choose a whole chapter to do flashcards on you could just choose a topic, this way you won't have to waste time going over the parts you feel confident about.
53	I would change how many questions are in each section. It's a lot to cover at one time.
54	I would take away the how sure are you of this question before you answer, because its relevance does not seem very important.
55	The length and how it adds questions when you get questions wrong.
56	That sometimes I get kicked out due to some random time restraint that is based on login time.
57	If LearnSmart is something that you have to pay for I would make it “free” to the student.
58	I wouldn't really change anything I like the way it works.
59	It could be publicized more.
60	Nothing, I love LearnSmart.
61	I would like the questions to be more relevant to what we're learning in class, instead of being more about the book and containing information that we don't cover.
62	Some of the questions are not really related to the course that I am taking so I often have to go back to the textbook to answer them and then the question is never addressed in class or on the test. It would be much more beneficial if the tests were filtered by what course you were taking.
63	I can't think of any improvements I would make to LearnSmart.
64	I guess just putting page numbers on where I can find the answers on the question or answer.
65	I do not particularly believe there is much improvement needed. It makes sure that you take in all of the correct information and can recall it when asked, which is what students need in order to succeed on an exam.
66	I hate that it costs so much money for the full program.
67	It would be great if the program is free, the cost seems a bit much for college students
68	i enjoyed it very much, don’t change a thing.
69	be able to print off the right answers
70	Nothing really.
71	Some of the questions topics Mr. Barbee has never taught before, so I sometimes get confused.
72	I think that it has a good format and I would not change anything that I have encountered so far.
73	The amount of material dealing with each subject.
74	Access. Some students cannot afford to pay the amount to actually have access to using LearnSmart so they may have a more difficult time understanding the work.
75	Sometimes it gets stuck and you have to log out and log back into it. If that would stop it would be nice.
76	i won’t change anything about learn smart it’s a good tool for students
77	I would make LearnSmart a free learning tool.
78	More questions
79	I would make more little foot notes, maybe a better summary of how to apply some things we learn to everyday situations.
80	The way you have to say if you know the answer, it should be yes no maybe.
81	Maybe it could have more options for ways to study the information, like games or strictly through some notes.
82	I would only change the fact that if you get an answer wrong then you have to repeat

	it. Although I think it's a great thing that you have to repeat the question till you get it right many people don't spend hours on questions that they get wrong. They are more likely to just quit instead of keep going on the questions since there are lots of them. I think if you get them wrong then you should be given the right answer right away and just move on.
83	I would ask more questions about material in the book instead of just a majority of the pictures that are in the book. Overall I really enjoy LearnSmart and there aren't a lot of things you should change.
84	I would like to be able to repeatedly do the quizzes over again after I have finished them. I would also like to see the teacher be able to change the quizzes to better suit the course the teacher has set.
85	I would like to change how many times you can complete a group of flash cards. It always stops once you've completed the set.
86	Incorporate more study-based activities instead of just flash cards.
87	Nothing, its preparation and easy to use is quite beneficial. Don't change anything that doesn't need to be!
88	Nothing.
89	I would like to see more ways of teaching other than just asking questions.
90	I wouldn't change anything because I don't know how this works
91	I think it is fine the way it is.

Table B3. Question 3 Responses (Do you think using LearnSmart activities has improved your performance in this class?).

Response	Number of Students	Percent of Total Responses to this Question (out of 92)
Yes	69	75 %
No	23	25%

Table B4. Question 4 Responses (Approximately how much time do you spend per week using LearnSmart?).

Response	Number of Students	Percent of Total Responses to this Question (out of 92)
Less than 1 hour	53	57.61%
1-2 hours	34	36.95%
3-5 hours	5	5.43%
More than 5 hours	0	0%

Table B5. Question 5 Responses (How is LearnSmart being used in your class?)

Response	Number of Students	Percent of Total Responses to this Question (out of 91)
It is a non-graded supplement to lecture	81	89.01%
It is a required graded part of class work	1	1.10%
It is extra credit	9	9.89%

Table B6. Question 6 Responses (Do you use LearnSmart activities to prepare for exams in this class?).

Response	Number of Students	Percent of Total Responses to this Question (out of 92)
Yes always- 100% of the time	23	25%
Yes often- about 80% of the time,	15	16.30%
Yes sometimes- about 50% of the time	36	39.13%
No never	18	19.56%

VITA

Lauren Alexandra James was born at Fort Stewart, Georgia, on February 6, 1985. She attended elementary school first in Westerville, Ohio, and then at Fort Bragg, North Carolina, before graduating from Terry Sanford Senior High School in Fayetteville, North Carolina in June of 2003. That fall, she began her undergraduate studies at Appalachian State University in Boone, North Carolina where she was a Chancellor's Scholar. She was graduated in August of 2007 with a Bachelor of Arts in Biology. She continued to work as a restaurant manager at a local Boone restaurant before accepting a teaching position in New York City with Teach for America. She taught high school biology in Brooklyn and the Bronx. In the fall of 2010, Ms. James began her studies towards a Master of Science degree in the Department of Biology at Appalachian State University. The M.S. was awarded in May 2012.

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